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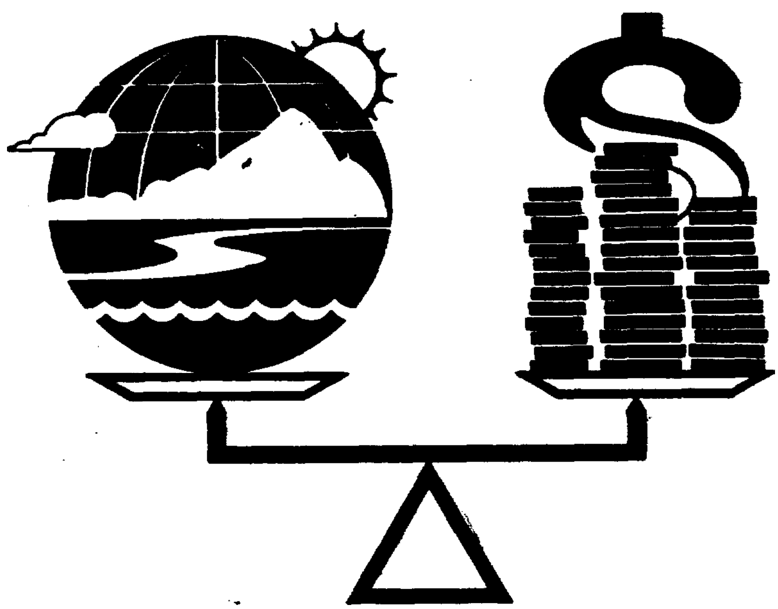
Contingent Valuation Assessment Of The Economic Damages Of Pollution To Marine Recreational Fishing



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Contingent Valuation Assessment of The Economic Damages of Pollution to Marine Recreational Fishing

Submitted to:

Mary Jo Kealy

office of Regulatory Management and Evaluation

U.S. Environmental Protection Agency

Washington, D.C. 20460

Submitted by:

Trudy A. Cameron

Department of Economics

University of California, Los Angeles

405 Hilgard Avenue

Los Angeles, Ca. 90024

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CONTINGENT VALUATION ASSESSMENT OF THE ECONOMIC DAMAGES OF POLLUTION TO MARINE RECREATIONAL FISHING

(EPA Cooperative Agreement # CR-814656-01-0)

Trudy Ann Cameron

Executive summary

The research performed under this cooperative agreement is summarized in the contents of four papers. These are described in the following sections.

1. 'The Determinants of Value *for a Marine* Estuarine Sportfishery: The Effects of Water Quality in Texas Bays," (also Working Paper #523, Department of Economics, University of California at Los Angeles).

This paper gives a detailed description of the data collected in the socioeconomic portion of the Texas Parks and Wildlife Creel y 10,000 recreational anglers between May and November of 1987. It also summarizes the auxiliary data sources used to augment these data, which include gamefish abundance estimates we have calculated from the data collected in the Texas Parks and Wildlife Resource Monitoring Program, water quality data from the Texas Department of Water Resources, and five-digit zip code sociodemographic averages from the 1980 Census.

The objective in this first paper is to formulate special statistical models that produce estimates of each individual survey respondent's willingness to pay for access to the recreational fishery in the eight major bays along the Texas Gulf Coast. In this paper, no attempt is made to force these models to conform with formal economic theories. Instead, minimally sophisticated discrete choice econometric medals are use'd in an attempt to establish the apparent systematic relationships between willingness to pay and whatever explanatory factors are available. These factors include: characteristics of the individual, their current catch, location and time of the interview, typical gamefish abundance, and coarse measures of several dimensions of water quality by time and location collected both by survey personnel and separately by the Department of Water Resources.

The econometric methods used in this analysis are specially designed to accommodate the "limited dependent variable" nature of the data. The paper describes the mathod by which maximum likelihood logit estimates can be transformed to yield the implied parameters of anapproximation to the demand function for recreational fishing access. In particular, we are interested in price and income elasticities of demand. But we also focus in this study on the extent to which water quality, geographical and seasonal dummy variables, socioeconomic and other variables act as shifters of this demand function.

For this portion of the study, there are mixed findings concerning the effects of water quality on the value of the recreational fishery. A wide variety of meteorological data and data on water quality is available. In most cases, however, it was necessary to aggregate these data up the level of each of the eight major bays and for each month of the sample For example, we know about average temperature, dissolved oxygen, turbidity, etc., as well as nitrogen nitrate levels, phosphate levels, non-filterable residues, oil and gas in bottom deposits, and a wide array of other qualities.

While several of our water quality variables appear to make statistically significant contributions to explaining willingness to pay for fishing access, many of them have counter-intuitive signs. It can be inferred that water quality probably varies *inversely* with other unmeasured attributes of anglers and the fishing resource that directly affect the value of the fishery. For example, if there are fewer substitute recreational opportunities in the Houston area, recreational fishing opportunities may be valued very highly, but simultaneously, the water quality may be very low. The reverse may be true in more remote areas of the coast. If we include water quality, but omit alternative recreational opportunities (for lack of data), then, it will appear that lower water quality implies higher social values of the fishery. I suspect that something like this is precisely what is happening.

This study represents an heroic effort to assemble the most appropriate water quality data for the Texas Gulf Coast available from many different sources. Countless hours went into matching and merging all of this information with the survey responses. Unfortunately, it is an empirical issue whether or not the anticipated relationships will show up in these data. This paper concludes that it will be necessary to control for other important determinants of value before the residual variation attributed-to measured water quality can be unambiguously identified. *However*, there is ‘definite evidence that respondents perceptions regarding environmental quality are more immediate determinants of value than the actual measured quality of the water.

While water quality apparently cannot be considered in this much detail with the current dataset, other coarser sociodemographic variables, such as income, appear to have strong and intuitively plausible *effects on* values. The apparent price elasticity of demand for fishing days (if a market existed) appears *to* be roughly -2.2, meaning that if access cost anglers 1% more, demand would decrease by 2.2%. The income elasticity appears to be just less than unity, implying that recreational fishing opportunities are borderline between being necessities and luxuries.

There are other implications of these models, also conditional on the quality of the data. For example, geographical heterogeneity in the demand for recreational fishing davs does seem to exist. The water quality variables, collectively, seem to explain quite a lot of this geographic variation, even if multicollinearity among these variables limits our ability to attribute value diffe renices to specific individual dimensions of water quality.

The Non-market Value of Water Quality Attributes: Estimates for Texas' Marine Estuarine Sportfishery

by

Trudy Ann Cameron

1. Introduction

Decisions regarding the expenditure of public funds to enhance or restore environmental assets have frequently been made on the basis of purely normative arguments. Until recently, the non-market benefits enjoyed collectively by the consumers of environmental resources have been difficult co determine. The objective in this paper is to quantify the effects of variations in water quality upon the non-market value of the marine recreational fishery along the Texas Gulf Coast. Knowing how water quality affects the social value of this fishery will allow us to simulate changes in that value as a consequence of policies which improve water quality (or as a result of decisions to allow water quality to deteriorate).

The "travel cost" method (TCM) for valuing non-market resources has been widely used but is frequently inappropriate for a marine sportfishery because the point-to-point distance for these fishing trips is ***often*** poorly defined. Destinations are diffuse and true opportunity costs for access are difficult to measure. These problems with the travel cost method have made hypothetical or "contingent" market surveys popular for eliciting resource values.

In contingent valuation (CV) surveys, it seems to be particularly difficult for respondents to state the precise value they would place on the resource. Consequently, • variety of value elicitation techniques are employed. Different strategies are suitable depending upon whether the investigation relies upon personal interviews, telephone interviews, or mailed questionnaires.

One method is verbal "iterative bidding." An elaboration of this method, useful for in-person interviews or mail surveys, is the "payment card, " where the respondent is merely asked to scan a card and to indicate the highest amount willingly paid (or lowest compensation willingly accepted) for access to the resource. An extreme form of the iterative bidding strategy involves only the first iteration: a single randomly assigned value is proposed and the respondent decides whether to "take it or leave it," much as in ordinary day-to-day market transactions. This "closed-ended CV" or "referendum" question format economizes greatly on respondent effort and minimizes strategic bias, but reduces estimation efficiency. The single offered sum is varied across respondents, which allows the yes/no responses to these questions to imply both the location and the scale of the conditional distribution of valuations. Many more responses are required to generate equally statistically significant parameter estimates for the valuation function, but it is suspected that this value elicitation technique minimizes the wide array of biases which have bean ● rgued to plague the other CV elicitation methods.

At present, contingent valuation investigations are probably the most practical way to quantify the economic benefits to ● recreational fishery of pollution control activities. CV questions can often be appended quite easily to regular creel survey instruments, so the marginal cost of gathering CV data is relatively modest.

In CV valuation models, respondents' valuations of the resource are presumed to depend upon (a.) characteristics of the respondent and (b.) attributes of the resource (in this case, including the level of pollution and indirect manifestations of pollution levels such ●s the degree of urbanization and catch rates). A calibrated CV model can be used to simulate both (a.) the randomly chose a starting value from the list $50, $100, $200, $400, $600, $800, $1000, $1500, $5000, and $20,000, In addition, respondents were queried regarding actual market expenditures during the current trip: "How much will you spend on this fishing trip from when you left home until you get home?" This is as close as we can get to a measure of "travel cost."

The same basic criteria for deleting particular observations are applied in this paper as are described in Cameron (1988a). The same caveats regarding the sample also apply in this case. The sample employed in this study is slightly smaller only because our gamefish abundance data are drawn from a separate source: the Resource Monitoring Program of Texas' Department of Parks and Wildlife. We have their data only for April through the end of November, so the few December interviews in the survey sample were simply dropped.

The Resource Monitoring Program uses several types of fishing gear: gill nets, bag seines, beach seines, trawls, ●nd oyster dredges. The Program involves vast numbers of samples being drawn across the entire Gulf Coast. For 1983-1986, we had *over* 23,000 samples, with complete records of the numbers of individuals of each species collected in the sample. Since low temperatures in 1984 resulted in ● substantial fish kill along the Texas Gulf Coast, we utilize only those samples drawn in 1985 and 1986 to construct our abundance measures. Also , only gill nets capture the types of fish that recreational anglers would be seeking, so we use only the catch using this gear type. Still, we have roughly 5400 samples to work with.

One problem, however, 1s that gill nets were apparently not used during the months of July and August. So we must fill in for missing data for these two months. Fortunately, for each month and each of the eight major bay systems along the coast, we typically have between 40 and 80 samples in each of the two years. Once we have computed mean "catch per unit effort" for each month and each bay, the time series for the April-November data is fairly

Readers are referred to Cameron (1988a) for a vital preface to this research. We avoid extensive duplication in this paper by presuming readers are familiar with the findings of the earlier paper.

2. Outline of the Specification

As before, we will adopt the quadratic family of utility functions, for the same variety of reasons explained in the earlier paper. We will let U denote direct utility, Y will be income, and M will be current fishing day expenditures ("travel costs", roughly). Also, q will be the number of fishing days consumed and z (= Y - Mq) will denote consumption of other goods and services. We will let A denote the abundance of red drum, the primary gamefish species. The quadratic direct utility function will thus take the form:

$$U = \beta_1 z + \beta_2 q + \beta_3 z^2/2 + \beta_4 zq + \beta_5 q^2/2, \tag{1}$$

where the β_j are no longer constants, but will be allowed to vary linearly with the level of A: $\beta_j^* = \beta_j + \gamma_j A$, $j=1,...,5$.

3. Data

The data used *for* this model consist of a 3318 observation subset of the 3366 observations used in the earlier paper. The data come from an in-person survey conducted by the Texas Department of Parke and Wildlife primarily between May and November of 1987 (although there are a few observations for the first days of December). The primary purpose of the survey is to count numbers and species of fish making up the recreational catch, but during this particular period, additional economic valuation questions were posed to respondents.

In particular, the contingent valuation question took the form: "If the total cost of all your saltwater fishing last year was ____ more, would you have quit fishing completely?" At the start of each day, interviewers smooth for the seven most usual species of game fish (red drum, black drum, spotted seatrout, croakers, sand seatrout, sheepshead, and founder). We have used quadratic approximations for the May-October range of the data to fill in abundance estimates for the two missing months.

Preliminary atheoretic logit models based upon the contingent valuation data suggest that among the top three recreational target species--red drum, spotted seatrout, and flounder--only variations in the number of red drum have a statistically significant effect upon the implied value of a recreational fishing day. Consequently, we elect to employ ***only the*** abundance of red drum as a control for resource quality in this study.

The means and standard deviations for both the full sample of 3366 and the subset of 3318 responses●re given in Table 1. As can b. seen, the subset is still representative of the larger sample.

4. Utility Parameter Estmates

To assess whether or not the preference function differs systematically with the level of gamefish abundance, we estimate two models. First, we re-estimated the "basic" joint model from the earlier paper using just the subset of 3318 observations. This specification constrains the β coefficients to be identical across ●ll levels of gamefish abundance. Then we generalize the model by allowing each β to be ●linear function of A, which involves the introduction of five new a parameters. Since the "basic" specification is a special case of the model incorporating heterogeneity, a likelihood ratio test is the appropriate measure of whether A "matters." Results for the two models are presented in Table 2. The LR test statistic is 8.18. The 58 critical value for a $X^2(5)$ distribution is 11.07, and 10% critical value is 9.24. Thus the LR test just fails ***to reject*** independence of the utility function from the abundance of gamefish. (However, if one were to generalize the utility function to include only the interaction term zA and its coefficient γ_1, and

Table 1

Descriptive Statistics for Full Sample and “Gamefish Abundance” Subset

Variable	Description	Full Sample (n- 3366)	Subset (n- 3318)
Y	median household income for respondent’s 5-digit zip code (in $10,000) (1980 Census scaled to reflect 1987 income; factor-1.699)	3,1725 (0.6712)	3,2772 (0.6705)
M	current trip market expenditures, assumed to be average for all trips (in $10,000)	0.002915 (0.002573-)	0.002927 (0.002576)
T	annual lump sum “tax” proposed in CV scenario (in $10,000)	0.05602 (0.04579)	0.05608 (0.04576)
q	reported total number of salt water fishing trips to sites in Texas over the last year	17.40 (16.12)	17.37 (16.14)
I	indicator variable indicating that respondent would choose to keep fishing, despite tax T	0.8066 (0.3950)	0.8071 (0.3946)
A	Resource Monitoring Program, catch per unit - effort of red drum (gill nets) by month and by major bay system		0.1487 (0.06161)

none of the other variables or 7 coefficients, the incremental improvement in the fit of the model would be statistically significant. The 0.5 percent critical value of a $X^2(1)$ distribution is only 3.84.)

5. Implications of Fitted Parameter Estimates

In the earlier paper, several properties of the estimated models were recommended for attention. Here, the properties of the fitted utility function vary across levels of gamefish abundance, A. Consequently, we will examine the fitted utility function at the subsample mean of A (______) as well as at several other benchmark levels. It is entirely possible to compute values for several interesting quantities for each individual in the sample. Here, however, we will focus initially on the "mean" consumer.

Table 3 summarizes several properties of the fitted utility function for the several levels of gamefish ●bundance. As ● xpected, changes in gamefish abundance substantially ● ffect the value respondents place on access to this fishery. Value in this case is measured several ways. Compensating variation (CV) is the amount of additional income ● respondent would require, *if* denied *access* to the resource, to make their utility level the same as that which could be achieved with the optimal level of ● ccess. Equivalent variation (EV) is the loss of income which would leave the respondent just as much worse off as would ● denial of access. We also compute the equivalent variation for partial reductions In the level of ● ccess.

A visual depiction of the *effect* of gamefish abundance on the preferences of anglers (defined over fishing days and all other goods) is provided in Figure 1 for A = 0.1 and for A = 0.2. As anticipated, indifference tunes for A - 0.2 have considerably greater curvature, implying that anglers are less willing to trade off fishing days for other goods when gamefish abundance is higher. In contrast, with lower abundance, the curvature is considerably less, implying that under these circumstances,

Table 2

Parameter Estimates for "Basic" and "Gamefish Abundance" (A) Models

Parameter	Basic Model (n = 3318)	Abundance Model (n - 3318)
β_1 (z)	3.192 (7.968)	5.039 (6.266)
β_2 (q)	0.1191 (19.18)	0.1133 (10.87)
β_3 ($z^2/2$)	-0.08953 (-1.056)	-0.2622 (-1.322)
β_4 (zq)	0.002661 (1.967)	0.004570 (1.164)
135 ($q^2/2$)	-0.006862 (-22.16)	-0.006920 (10.31)
γ_1 (zA)	-	-12.85 (-2.390)
7_2 (qA)	-	0.03166 (0.5281)
γ_3 ($z^2A/2$)	-	1.191 (0.6256)
γ_4 (zqA)	-	-0.01112 (-0.4287)
γ_5 ($q^2A/2$)	-	0.0004552 (0.1137)
υ[a]	16.03 (81.46)	16.03 (81.38)
p	0.2354 (9.187)	0.2343 (9.033)
Log L	-15485.96 .	-15481.87[b]

[a] See Cameron (1988a) for discussion of the μ and p parameters.
[b] χ^2 test statistic is 8.18; at 10% level, $\chi^2(5)$ - 9.24.

We may be especially interested in the derivative of this fitted demand function with respect to E. It will depend not only on F and Y, but also on the level of E itself:

$$(3)\ \partial q/\partial E = \{[2(\beta_4+\gamma_4 E)F - (\beta_3+\gamma_3 E)\ F^2 - (\beta_5+\gamma_5 E)]\ [\gamma_2 + \gamma_4 Y - \gamma_1 F - \gamma_3 FY] - [(\beta_2+\gamma_2 E) + (\beta_4+\gamma_4 E)Y - (\beta_1+\gamma_1 E)F - (\beta_3+\gamma_3 E)FY]\ [2\ \gamma_4 F - \gamma_3 F^2 - \gamma_5]\}\ /\ [\ 2(\beta_4+\gamma_4 E)F - (\beta_3+\gamma_3 E)\ F^2 - (\beta_5+\gamma_5 E)\ ]^2.$$

This formula is untidy, but can be readily computed. Table 4 gives the values of this derivative as well as the corresponding elasticity, $(\partial q/\partial E)(E/q)$, for the full range of integer values of E which are possible in the data.

A visual display of the effects of changes in E upon the configuration *of* the fitted inverse demand curve for ●n individual with mean Y and F is presented in Figure 2. Observe that, ● lthoush the demand ***function can*** be highly non-linear in F, the fitted values of the parameters (for these data and in combination with the sample mean ● ngler characteristics) yield demand functions which are ● lmost linear, Each fitted demand curve passes through the value ***of F*** ● nd the corresponding particular fitted value of q* (for each E) ***for*** this representative consumer. Notice *that variations* in E, in the fitted model, have rather dramatic ● ffscts upon the implied choke price for access to the resource: the better the ● nvironmental quality, the higher the choke price.

The variation in the configuration of preferences, and the obvious shifts in the demand curves ● s ● function ***of*** E imply that the social value of ● ccess to the fishery will depend upon the subjective level of ● rwironmental quality ● t *fishing sites.* To illustrate this sensitivity, we have computed the ● quivalent variation for ● complete loss of access to the resource, as ● function of E, for a representative consumer with sample mean levels of Y ● nd

Table 4

Optimal Demand, Derivatives ●nd Elasticities
wrt Environmental Quality
(evaluated at mean Y and F, n = 3366)

E	q*	$\partial q/\partial E$	$(\partial q/\partial E)(E/q^*)$	EV for complete loss of access
1	14.72	0.2876	0.01953	$ 1046
2	14.97	0.2260	0.03018	1264
3	15.18	0.1822	0.03601	1499
4	15.34	0.1501	0.03912	1751
5	15.48	0,1257	0.04060	2022
6	15.60	0.1068	0.04110	2314
7	15.70	0.09193	0.06100	2630
8	15.78	0.07993	0. 04052	2971
9	15.86	0.07014	0.03981	3340
10	15.92	0.06204	0.03896	3741

F. These equivalent variations are also given in Table 4. Bear in mind that the range *of* E from 6 to 10 accounts for approximately one standard deviation on either side of the mean value reported in the sample. The EV estimates in Table 4 suggest that for a typical ●ngler, improving ●nvironmental quality from the "6" level to the "10" level would ●dd ●pproximately $1400 to the annual value of access to the fishery (an increase of over 50%).

This value must be considered in relation to the ●ctual distribution *of* *E* values in the sample. Tables 5 ●nd 6 give the details of these responses. Almost 40% of the sample is completely satisfied with current environmental quality. This suggests an alternative "simulation" based on the fitted model. Instead of simply considering the mean ●ngler, it is ●lso possible to simulate changes in E for each individual angler in the sample. Under current conditions, the equivalent variation for a complete loss of ●ccess varies over the sample from $648 to $4235, with ●mean of $3037 and●standard deviation *of* $778. If we take ●very respondent who reported ●subjective ●nvironmental quality level of less than 10 ●nd increase their value of E by one unit, the distribution of these ***fitted*** equivalent variation values can be expected to change. In fact, the new fitted values vary from $839 to $4238, with ●mean of $3253 and ●standard deviation of $71S. Thus the increase in the mean of the ●quivalent variations, whenwe improve by on. unit the●xperiences of those who were less than completely satisfied experience currently, is ●pproximately $216. If we could scale this up to the●ntiro population, this represents an increase in the social value of the fishery of ●pproximately 6.6%.

6. Subjective Environmental Qualities as a Function of Physical Measures

The subjective ●nvironmental quality question on the Texas Parks ●nd Wildlife Survey● licits information ●bout overall●nvirornntsl quality. We

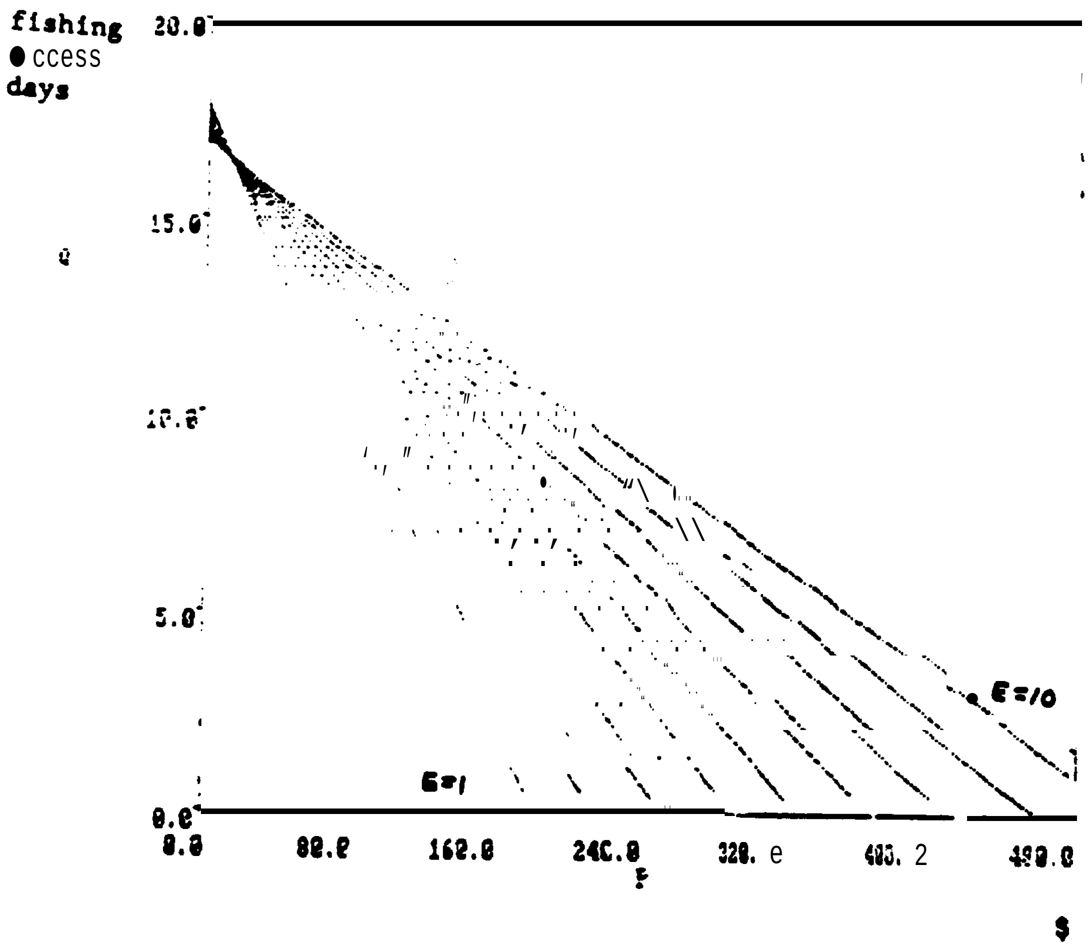

Figure a. Effects of increasing subjective ● uvirormon-1 quality on inverse demand curve for an angler with sample mean characteristics.

do not presently have access to typical or specific air quality measurements for different areas along the Texas Gulf Coast, but in the course of related research (Cameron, 1988b), we have attempted to determine how a variety of water quality measures ●re related to respondents' subjective ●ssessments of environmental quality.

From ● variety of auxiliary sources reported In Cameron (1988b), including the Texas Department of Water Resources, and the Resource Monitoring division of Texas Parks and Wildlife, *we* have obtained data on the characteristics of tens of thousands of water samples over the few years up to and including the time period of the valuation survey. Most of the water quality "parameters" have been averaged by month ● nd by ● ach *of* the ● ight major bay systems along the Texas ***Gulf Coast. A*** few ● re ● vailable only by bay system. (See the original document for details.)

Table 7 reproduces the results for E regressed on ● variety of water quality parameters in an ● ***d hoc*** specification. Not surprisingly, the relationship between the subjective environmental quality measure and "typical" water quality is quite weak. For this reason, we do not devote space in this paper to ● discussion of the ● xplanatory variables. The reader is referred to Cameron (1988b) for this information. Certainly, many more physical factors will ● ffect perceptions than simply the few for which we have measurements. Attributes of the respondent can ● lso b. ● xpocted to have some impact upon the subjective assessments of ● mlronmental quality. Other regressions reported in the ● ppendices *of Cameron* (1988b) ● xamine the influence of socioeconomic variables on these responses. They ● lso ● stablish the presence of sow seasonal and geographical variation.

Table 7

OLS Regression of "Ability to Enjoy Unpolluted Natural Surroundings: on Measured Water Quality Variables

F-TEST	4. 247
OBS	695

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER-O
INTERCEP	8.334	1,860	4.481
MTURB	0.001600	0.01016	0.158
MSAL	0.01851	0.01795	1.031
MDO	-0.2415	0.1387	-1.742
TRANSP	0.02034	0.01311	1,551
DISO	0.2204	0.1077	2.047
RESU	0.005304	0.006889	0.770
NH4	6.053	3.659	1.654
NITR	-2.236	1.155	-1.936
PHOS	2.357	1.700	1.386
CHLORA	-0.002728	0.02576	-0.106
LOSSIGN	-0.009637	0.02440	"0.395
OILGRS	-0.003734	0.001145	-3.261
CHROMB	0.02663	0.02361	1.128

The Vietnamese, as opposed to other cultural groups, seem to have markedly different preferences for fishing than the population as a whole. Money spent on associated market goods, once thought to be a reasonable proxy for the non-market value of a fishery, is positively related to the value of a fishing day (but typically completely unrelated to catch **rates)**. Importantly, many other explanantory variablees make strong contributions **to exp**laining the annual value of fishing day access; re**liance** solely upon market expenditures could severel**y misstate resource values.**

The preliminary specifications explored in detail in this paper produced results that were sufficiently provocative to warrant further analysis of these data. It was decided that *placing a little more* structure on the model might help. Hence the next paper.

2. "Combining Contingent Valuation and Travel Cost Data for the Valuation of Non-market Goods," (a retitled major revision of Working Paper #503, Department of Economics, University of California at Los Angeles).

This second paper takes advantage of the general sense of the data derived from the extensive exploratory modeling described *in* the first paper. It has been determined that there are several apparently robust systematic relationships between willingness to pay for access to the fishery and other measurable variables. With this established, one can be more confident that it is worthwhile to undertake further mo**deling** that is more solidly founded upon neoclassical macroeconomic principles.

I am very pleased with the quality of this paper. It develops a new methodology, employing novel and very sophisticated econometric techniques appropriate to the special features of the data. The analysis is particularly care ful and rigorous and many tangential issues are considered thoroughly.

The simplest model of consumers' utility maximization posits that consumers have preferences defined over two types of commodities: the good in question sportfishing days) and a composite of all other goods and services. More of both of these things makes them happier, but they are constrained by their budgets. They must trade off other goods and services in order *to* consume an additional fishing day, and vice *versa.* They allocate their limited budge ts between fishing days and other things so as to maximize their level of happiness.

All models of this type are, of course, dramatic simplifications of the real world, but they frequently provide very useful insights into the essential features of consumer behavior. Individuals with different sociodemographic characteristics, under different resource conditions, will make different consumption decisions. This type of variation allows us to calibrate a model which can then be used to simulate the likely responses of particular types of individuals if their decision making environment changes. **Wh**ile these models cannot be expected to do very well in predicting the actual response of *a* specific individual to some change, they can perform fairly well in the aggregate.

Earlier research employing these “utility-theoretic” models for the valuation of a non-market good such as sportfishing access occasionally used a technique known as the travel cost method. If fishing days can be considered as a single homogeneous good, information on the cost of a single trip and the number of trips taken can be combined to yield a model of demand for fishing days. This is the relationship between the implicit price of access and the number of days demanded, with accommodation for whatever shift factors (income, resource quality, etc.) can be quantified.

Other attempts to value recreational fishing days have relied upon “contingent valuation” survey techniques, where survey participants are queried about the decisions they think they would make if a hypothetical market for fishing days existed (i.e. if they had to pay a per-day entrance fee or purchase a season’s pass to fish). The discrete choice form of contingent valuation question was posed on the Texas parks and Wildlife Creel Survey. Respondents’ answers about whether or not they would be willing to pay an arbitrarily selected annual fee to continue fishing were analyzed in ad hoc models in the first paper discussed above.

In the paper being described here, however, the mathematical form of the discrete choice model is carefully selected to conform to an underlying family of consumer preference functions with desirable propert ies from the point of view of economic theory. By doing this, the calibrated models can ultimately be solved to yield corresponding estimates of the formal welfare measures of value, including equivalent variation and compensating variation.

The primary methodological innovation in this paper is to combine both travel cost and discrete choice contingent valuation data in one comprehensive model. Both methods of eliciting valuation infromation from survey respondents should provide insights regarding the same Preference structure. We can combine the two different perspectives for a more thorough characterization of consumer behavior.

In the basic model in this paper, all fishing days are treated as homogeneous and consumer choices regarding fishing access depend only upon their taste for fishing. their incomes, and the price of access to a fishing day. When this model is explored thoroughly and shown to be relatively successful, the assumption that all fishing days are identical is relaxed.

The illustrative generalization explored in this paper is to allow preferences for fishing days (versus all other goods and services) to vary systematically with the zip code proportion of people reporting Vietnamese heritage on the 1980 Census. This is an imperfect measure of the respondent’s own sociodemographic category, but we anticipate at least some correlation. The proxy turns out to be a significant shifter of preferences. The higher the proportion Vietnamese, the less willing is a representative consumer to trade off fishing days for other goods. Likewise, the greater will be their demand for fishing days at any relative price and the greater would be the cost to them of having to forgo some or all of their fishing access.

The paper provides detailed empirical estimates of the welfare values associated with changes in fishing access. However, these dollar values are conditional upon the extent to which the data we are using actually capture the concepts prescribed by the microeconomic theory underlying the

8. Conclusions

Clearly, there is good evidence that angler's value of the fishing experience is affected by their subjective assessment of environmental quality. For this small sample from the Texas survey, allowing for heterogeneous preferences which vary with environmental quality makes a statistically significant improvement in the economocric model at almost the 5% level. Despite the fact that we have lumped all other goods in the consumption bundle into a single composite, the ***fundamental regularity*** conditions for a utility-theoretic model are satisfied. Of course, all *of* the caveats mentioned in Cameron (1988a) and Cameron (1988b) also apply to this analysis, so the results must be interpreted with some caution.

Unambiguously, if anglers' **perceptions** of environmental quality can be improved, our model indicates that the social value of the resource will be increased (and vice versa, of course). What 1s clear, however, is that a better link must be forged between perceptions and actual physical quantities of pollutants (both air and water). We need to know just what It takes to raise someone's response from an 8 to a 9 on this type of Likert-scale question. This will require cooperation between physical and social scientists.

REFERENCES

Cameron, Trudy Ann, (1988a) "Empirical Discrete/Continuous Choice Modeling for the Valuation *of* Non-market Resources or Public Goods," Working Paper #503, Department of Economics, University of California •t Los Angeles, September.

Cameron, Trudy Ann, (1988b) "The Determinants of Value for •Marine Estuarine Sportfishery: The *Effects* of Water Quality in 'Texas Bays," Discussion Paper # Department of Economics, University of California •t Los Angeles, September.

specification. The data are far from ideal. Consequently, it would not be appropriate in this summary to uphold the dollar values as unambiguous. The Texas data are by far the best I had encountered up until that time. But it is crucial that this set of papers be regarded as demonstrations of the types of analyses that can be conducted. If results as satisfying as these can be achieved with mediocre ingredients, then subsequent surveys can be conceived and implemented to take maximum advantage of the methodological framework. These future studies will undoubtedly produce final empirical value estimates which can more confidently be used as a basis for policy making.

With these qualifications, and others described carefully in the paper, some of the welfare estimates can be mentioned. For example, according to the basic model, if fishing days were curtailed by 10%, the average survey respondent would lose an amount of satisfaction roughly equivalent to the loss of $35 of income per year (although individual losses range from $19 to $52). A 20% curtailment would match an income loss of $139, on average. Simulating a complete loss of access is riskier and less realistic, but the model suggests that the average respondent would be hurt by about $3400.

Generalizing the model to accommodate sociodemographic heterogeneity (proportion Vietnamese in zip code) shows how the fitted preference function is markedly different (for an otherwise typical respondent) when this proportion ranges from O to 2%. Plots of the estimated "indifference curves" and budget constraints make these differences particularly obvious.

The paper also breaks new ground by freeing up certain parameter restrictions within the jointly estimated model so that the travel cost and contingent valuation data are allowed to imply different preferences. A scheme is also developed for allowing differential weighings in the pooling of these data, according to the perceived relative reliability of these two types of information.

3. "Using the Basic 'Auto-Validation' Model to Assess the Effect of Environmental Quality on Texas Recreational Fishing Demand: Welfare Estimates," (also Working Paper #522, Department of Economics, University of California at Los Angeles)

The initial exploratory study described above (which employed all of the available data and used ad hoc models) suggested that measured objective dimensions of water quality did not always have clear cut and intuitively plausible effects on willingness to pay for access to sportfishing opportunities. An alternative possibility is that people's preferences for sportfishing are affected by their perceptions of environmental quality, not by what is actually out there. (What you don't know won't hurt you?) The creel survey asked respondents' subjective opinions about whether they were able to enjoy "unpolluted natural surroundings." Answers were recorded on a scale of one to ten. In this supplemental paper, we allow preferences to take on systematically different configurations depending upon these answers.

Various welfare implications can be derived from the fitted model, again with the same caveats mentioned in the above two summaries. The amount of income loss that would be equivalent to a 10% cutback in access to the fishery is roughly $29 per year at the mean level of the subjective variable (8.07).

If environmental quality is perceived to be a 10, the loss would be about $37 per year. In contrast, if the quality is only 6, the loss of access would be only, $23. For a complete loss of access, the decrease in value at the mean, at 10 and at 6 would be about $2400, $3000, and $1900 respectively. (Note that only a smaller subsample of the data could be used for these models, since not all respondents were queried regarding environmental quality.)

Thus, we find that perceptions of environmental quality do affect preferences for fishing days as opposed to all other goods and services, and thus the value of access to the fishery will almost certainly be influenced by perceptible variations in water quality. Furthermore, we can show that respondents' answers to the "unpolluted natural surroundings" questions are statistically related to several of the measured water quality attributes examined in the first paper described above. However, it is clear that more research will be necessary to establish how objective water and environmental quality data can be translated into individual perceptions.

With infinite and free computing resources, it would be desirable to allow preferences to differ systematically according to the levels of a whole range of shift variables. At present, however, there was no budget for such an elaborate model, so we were limited to exploring single shift variables independently. (Each shift variable adds five new unknown model parameters to be estimated.)

4. "The Effects of Variations in Gamefish Abundance on Texas Recreational Fishing Demand: Welfare Estimates."

Keeping in mind the limitations on complexity, a second supplemental paper was also developed. Whether or not the value of this recreational fishery is dependent upon the abundance of gamefish is another question of vital interest ***to*** policy makers. Ideally, one would measure all of the major gamefish species (there are seven or eight, described in the first paper, above) . For this illustration, however, we opt to concentrate upon red drum.

As a measure of red drum abundance, we could have used each individual's reported catch of red drum on the fishing trip when they were surveyed, but this catch is dependent upon skill levels, which will be related to the individual's resource value. This is undesirable. Consequently, we rely upon data produced by the Parks and Wildlife Resource Monitoring program. We used data from the thousands of official samples collected by this program and aggregated up to average abundance measures by bay system and by month. These data are only proxies for the actual local abundance of red drum experienced by recreational anglers in each area and month, but they are completely unrelated to angler skill. Thus we hope to avoid simultaneity bias in the resulting estimates.

This model, augmented to control for red drum abundance, lets us explore the likely changes in the social value of access to the fishery when the abundance of red drum changes. Again subject to extensive caveats, we find that the income loss that would be equivalent to a 10% reduction in fishing access is roughly $35 at mean abundance of red drum. If abundance was higher by 20%, the same reduction would hurt anglers by an average of $40. If abundance was lower by 20%, the decrease in access would be equivalent to anglers consider other goods to be relatively better substitutes for fishing days. For example, when A = 0.1, the same change in the relative price of a fishing day will lead to a larger decrease in the optimal number of days consumed than when A - 0.2.

In addition to the properties of the utility function and its corresponding Marshallian demand functions, we might be interested in calculating the derivatives of these Marshallian demand functions with respecc to the level of the A variable. The Marshallian demand function for the model with heterogeneity is:

$$(2) \qquad q = [\ (\beta_2+\gamma_2 A) + (\beta_4+\gamma_4 A)Y - (\beta_1+\gamma_1 A)M - (\beta_3+\gamma_3 A)MY\ ]\ /$$
$$[\ 2\ (\beta_4+\gamma_4 A)M - (\beta_3+\gamma_3 A)\ M^2 - (\beta_5+\gamma_5 A)\ ]$$

Figure 2 plots the inverses of these fitted Marshallian demand functions ***(with ●ccess days*** q on the vertical axis, ●nd.tho price ***of access*** on the horizontal axis). These demand curves are drawn for an individual with mean income Y and mean travel costs M.

As A varies from 0.0 to 0.1 to 0.2 (compared to the actual mean value of 0.1487), these demand curves shift out further and further. Observe that, although the demand function can be highly non-linear in M, the fitted values of the parameters (for these dat a and in combination with the sample mean angler characteristics) happen to yield demand functions which are almost linear.

Notice that variations in A, in the fitted model, have rather dramatic effects upon the implied "choke price" (resonation price) for access ***to*** the resource: the grater the gamefish abundance, the higher the choke price. This can be interpreted ●s implying that with greater levels of preferred gamefish abundance, higher and higher prices for access wouldbe willingly paid before individuals will cease entirely to go fishing.

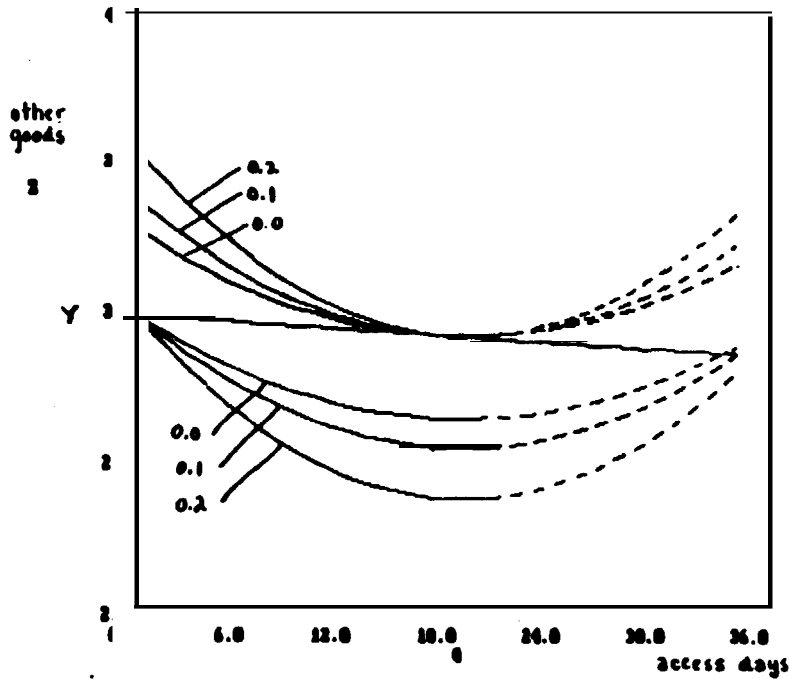

Figure 1 - Effects of changes In the abundance of the primary gamefish on *preferences* for fishing ●ccess days. Empirical indifference curves for mean consumer with abundance at 0.2, 0.1, a d0.0. (Actual mean - 0.149. standard deviation - 0.062. usable sample size n - 3310.)

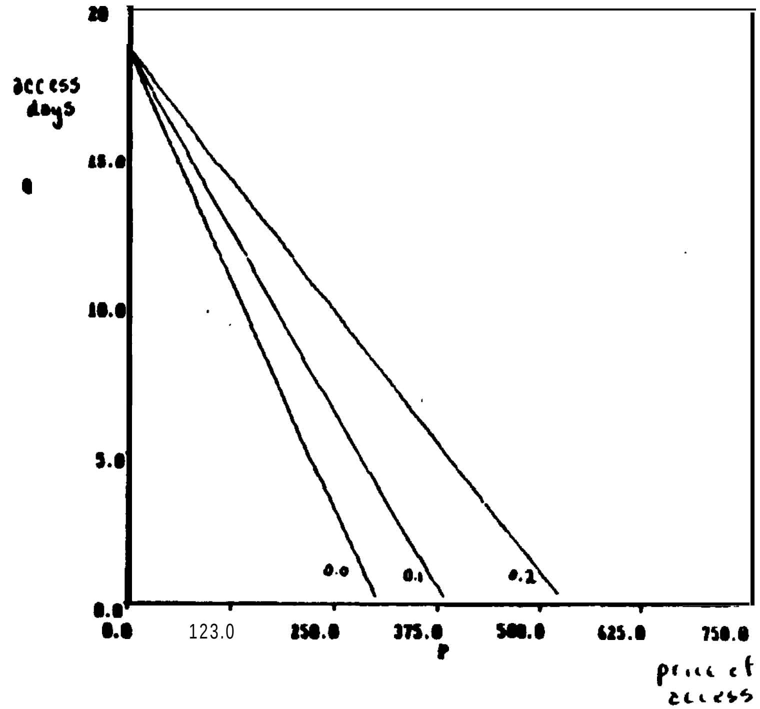

Figure 2 - Empirical inverse demand curves for fishing ● ccom days for mean consumer ●t primary gamefish ● brrmdace levels of 0.2. 0.1 ●nd 0.0. (Actual mean -0.169, standard deviation -0.062, usable ● mplo ● im n - 3310.)

Table 3 also gives the utility maximizing number of fishing days demanded, q, at the sample mean values of M and Y, as a function of the changing levels of gamefish abundance, A. Note that this optimal number of days is not very sensitive to A. This is a consequence of the fact that changes in A seem to have a substantial effect upon the curvature of indifference tunes; they have less of ●n effect on their location.

The variation in the configuration of preferences, and the obvious shifts in the demand tunes as a function of A imply that the social value of access to the fishery will depend upon the level of gamefish abundance at fishing sites. To illustrate this sensitivity, we can concentrate upon the equivalent variation for a complete loss of access to the resource, as a function of A, for a representative consumer with sample mean levels of Y and M. These variations can be detected by scanning ●cross the columns in Table 3. Table 3 suggests that for ●typical ●ngler, improving gamefish ●bundance (red drum only) by a factor of 1.5 times its current level of A - .1487 would increase the annual value of access to the fishery by ●bout 369 ●nd improving abundance by 1.2 would increase access values by about 12%. In contrast, decreasing abundance to 0.8 of its current level would decrease the annual value of access by about 10%; decreasing abundance to 0.5 of its current level would decrease access values by 22%. If it is safe to extrapolate these estimates (based on functionally “local” variations in actual abundance levels) to a scenario where red drum are completely eliminated, the loss in access values would be ●bout 37%. (Remaining value would derive from the catch of other species, and from the non-catch utility derived from fishing days.)

6. Discussion and Conclusions

As mentioned above, a full explanation of the empirical innovations embodied in the use of a joint contingent valuation/travel cost model for

Table 3

Propert ies of the Fi tted Utility Function (for "Mean" Consumer)
(n - 3318; valid sample with ● vailsbl. abundance data)

Propert y	● t 1.5(mean A)	● t 1.2(mean A)	● t mean A	● t 0.8(mean A)	● t 0.5(mean A)	● tA-o
utility Function Parameters:						
β_1^*	2.173	2.746	3.129	3.511	4.084	5.039
β_2^*	0.1204	0.1190	0.1180	0.1171	0.1157	0.1133
β_3^*	0.03545	-0.04961	-0.00504	-0.1205	-0.1736	-0.2622
β_4^*	0.002089	0.002586	0.002916	0.003247	0.003743	0.0045?0
β_5^*	-0.006510	-0.006838	-0.006852	-0.006865	-0.006886	.0.006920
Function Maximum:						
z*	-528.08	57.40	37.93	29.98	24.16	19.73
q*	-144.18	39.10	33.37	31.23	29.93	29.60
Demand Elasticity wrt						
price	-0.05569	-0.06598	-0.0?278	-0.07915	-0.08919	-0.1063
income	0.05568	0.07288	0.06428	0.09529	0.1121	0.1405
Optinal number of Access days (q)	17.65	17.45	17.31	17.17	16.97	16.62
Compensating Variation for Complete Loss of Access	$4873	$4046	$3620	$3266	$2835	$2299
Equivalent Variation for Complete Loss or Access	$4796	$3943	$3515	$3164	$2741	$2221
N for Access Restricted to O of Curent Fitted Level, for a -						
0.1	$3885	$3196	$2850	$2566	$2223	$1801
0.2	3069	2527	2254	2029	1758	1425
0.3	2350	1936	1727	1555	1348	1092
0.4	1726	1423	1270	1143	991	803
0.5	1199	988	882	795	689	558
0.6	767	633	565	509	441	357
0.7	431	356	318	286	248	201
0.8	192	158	141	127	110	89
0.9	48	40	35	32	2a	22

valuing a recreational fishery is given in Cameron (1989). This paper represents a specific generalization of the model which allows the parameters of the direct quadratic utility function to vary systematically with the level of just one species of gamefish. We have selected the most popular gamefish species (red drum). A more elaborate model, of course, could let the utility parameters vary systematically with any number of characteristics of the resource, not just the abundance of a single species of gamefish.

Since we concentrate only upon red drum abundance, even the reduction to zero of red drum stocks (in the most extreme simulation described in the last section) will not lead everyone to cease fishing entirely. Other species of gamefish will remain. In this specification, variations across location and month in red drum abundance may be correlated with the abundance of other species. If this is the case, our red drum abundance measure will be capturing variations in the abundance of more than one species. Nevertheless, we do not capture the distinct effects of any seasonal or location variation in species abundance that is uncorrelated with red drum abundance.

The simulated variations in red drum abundance used as illustrations in this paper are by far the coarsest simulations that could be generated by a model such as this. We have concentrated solely on variations in abundance as they would affect a representative consumer with mean income and travel costs. However, since each individual's estimated preference function depends on the abundance of red drum during the month and in the bay system in which they are fishing, the model is perfectly able to simulate the impact upon the value of fishery access to individuals of forecasted changes in red drum abundance either by month or by geographical area. As the configurations of individuals' indifference curves change, so will their optimal number of fishing days and the equivalent variation associated with partial or complete loss of access.

The intent of this paper, therefore, is to illustrate the versatility of the constrained, jointly estimated contingent valuation/travel cost model for recreational fisheries valuation. It is satisfying to find thoroughly plausible changes in economic quantities as a consequence of exogenous variations in resource characteristics. This generalization of the “common utility function” model to a “systematically varying utility function” model should serve as a very useful prototype for subsequent research.

REFERENCES

Cameron, Trudy Ann, (1989) "Combining Contingent Valuation and Travel Cost Data for the Valuation of Non-market Goods," a revision of "Empirical Discrete/Continuous Choice Modeling for the Valuation of Non-market Resources or Public Goode," Working Paper #503 (1988), Department of Economics, University of California at Los Angeles, September.

Cameron, Trudy Ann, (1988b) "The Determinants of Value for a Marine Estuarine Sportfishery: The Effects of Water Quality in Texas Bays," Discussion Paper #523, Department of Economics, University of California at Los Angeles, September.

Cameron, Trudy Ann (1988c) "Using the Basic 'Auto-Validation' Model to Assess the Effect of Environmental Quality on Texas Recreational Fishing Demand: Welfare Estimates," Discussion Paper #522, Department of Economics, University of California at Los Angeles, September.

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Using the Basic "Auto-validation" Model to Assess the Effect of Environmental Quality on Texas Recreational Fishing Demand: Welfare Estimates

by

Trudy Ann Cameron
Department of Economics
University of California, Los Angeles 90024-1477

ABSTRACT

In an extensive earlier paper (Cameron, 1988a) we developed a fully utility-theoretic model for the demand for recreational fishing access days, applied to a sample of 3366 Texas Gulf coast anglers. The model employs "contingent valuation" and "travel cost" data, jointly, in the process of calibrating a single utility function defined over fishing days versus all other goods and services. The theoretical specification (quadratic direct utility) and the econometric implementation will not be reproduced here. Instead, we focus specifically on the implications of an extension to this model. We employ a subset of 506 observations from the same survey for which respondents were asked to indicate their ex post subjective assessment of the environmental quality at the fishing sits. We allow the parameters of the underlying utility function to vary systematically with the perceived level of environmental quality to assess the impact of environmental factors on the demand for access days. Treating the 10-point response scale for environmental quality (E) as a continuous variable, we find (among other results) that for the average angler improving E from one standard deviation below the mean to one standard' deviation above increases the value of the fishery (measured by equivalent variation) by about $1400 (about 50%).

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Using the Basic "Auto-validation" Model to Assess the Effect of Environmental Quality on Texas Recreational Fishing Demand

1. Introduction

In Cameron (1988a), we derived ●nd ●stimated the parameters of ● quadratic utility function for ●trimmed sample of Texas Gulf Coast recreational fishermen. The utility function, in its simplest form, is defined over fishing ●ccess days ●nd all other goods ●nd services (income). The novelty of that paper is primarily its utilization of ●fully utility-theoretic framework for ●nalyzing both "contingent valuation" (CV) data (respondents anticipated behavior under hypothetical scenarios) and "travel cost" data (respondents' actual behavior in the consumption of ●ccees days). The latter form of data gives us ●feel for the consequences of small local variations in ●ccess prices; the former provides additional information, however hypothetical, regarding more drastic changes in the consumption environment.

The earlier paper develops the basic specification ●nd goes on to consider several extensions to that basic model: discounting the influence of the CV data in the estimation process; estimation without travel coet data (only income ●nd consumption); and the ●ccomaodstion of heterogeneous preferences. In the last category, we demonstrated that it is straightforward to ●dspt those models to ●now for systematic variation in the preference function according to geographical or sociodemographic factors.

In this paper, we will ●gain employ heterogeneous utility functions, but we will only be able to ●xploit a subset of the data.We wish to concentrate upon the potential ●ffects of respondents' perceptions ●bout ●nviromantal quality on their demand (valuation) of ●ccess to the recreational fishery.

Readers are referred to Cameron (1988a) for a vital preface to this research. We avoid extensive duplication in this paper by presuming readers are familiar with the findings of the earlier paper.

2. Outline of the Specification

As before, we will adopt the quadratic family of utility functions, for the same variety of reasons explained in the ●arlier paper. We will let U denote direct-utility, Y will be income, ●nd F will b. current fishing day expenditures ("travel costs", roughly). Also, q will be the number of fishing days consumed and z (- Y - Fq) will denote consumption of other goods and services. We will let E denote subjective environmental quality. The quadratic direct utility function will thus take the form:

$$(1) \qquad U = \beta_1 z + \beta_2 q + \beta_3 z^2/2 + \beta_4 zq + \beta_5 q^2/2,$$

where the β_j●re no longer constants, but will be●llowed to vary linearly with the level of E: $\beta_j^* = \beta_j + \gamma_j E$, j-1,...,5.

3. Data

The data used for this model consist of a 506 observation subset of the 3366 observations used in the ●arlier paper. The data come from an in-person survey conducted by the Texas Department of Parks and Wildlife between Hay and November of 1987. The primary purpose of the survey is to count numbers ●nd species of fish making up the recreational catch, but during this particular period, ●dditional ●conomic valuation questions were posed to respondents.

In particular, the contingent valusation question took the form: "If the total cost of ●ll your slatwater fishing last year was ____ more, would you have quit fishing completely?" At the start of each day, interviewers randomly chose ●starting value from the list $50, $100, $200, $400, $600,

$800, $1000, $1500, $5000, and $20,000. In addition, respondents were queried regarding actual market expenditures during the current trip: "How much will you spend on this fishing trip from when you left home until you get home?" This is as close as we can get to a measure of "travel cost."

The same basic criteria for deleting particular observations ●re ●pplied in this paper as are described in Cameron (1988a). The same caveats regarding the sample also apply in this case. The sample employed in this study is smaller only because the ex post subjective environmental quality questions were asked of only approximately one-eighth of the full sample. This question was just one of eight rotating questions on special issues.

The precise wording of the environmental quality question was "To what extent were you able to enjoy unpolluted natural surroundings [during this fishing trip]?" Responses were given on ● Likert-type scale of 1 to 10, with 10 being highest, The means ● nd standard deviations for both the full sample of 3366 ● nd the subset of 506 responses ● re given *in* Table 1. As can be seen, the subset is fairly representative of the larger sample.

4. Utility Parameter Estimates

To ● ssess whether or not the preference function differs systematically with the level of environmental quality, we ● stimate two models. First, we re-estimate the "basic" joint model from the ● arlier paper using just the subset of 506 observations. This specification constrains the β coefficients to be identical ● cross ● ll levels *of* ● mrirornntal quality. Then we generalize the modal by ● llowing ● ach β to b. ● linear function of E, which involves the introduction of five new a parameters. Since the 'basic" specification is a special case of the model incorporating heterogeneity, a likelihood ratio test is the ● ppropriate measure of whether E ● matters." Results for the two models are presented in Table 2. The LR test statistic is

Table 1

Descriptive Statistics for Full Sample and 'Environmental" Subset

Variable	Description	Full Sample (n - 3366)	Subset (n- 506)
Y	median household income for respondent's 5-digit zip code (in $10,000) (1980 Census scaled to reflect 1987 income: factor-1.699)	3.1725 (0.9995)	3.1681 (1.0134)
F	current trip market expenditures, assumed to be average for all trips (in $10,000)	0.002915 (0.002573)	0.003255 (0.002767)
T	annual lump sum "tax" proposed in CV scenario (in $10,000)	0.05602 (0.04579)	0.05661 (0.04770)
q	reported total number of salt water fishing trips to sites in Texas over the last year	17.40 (16.12)	15.78 (15.32)
I	indicator Variable indicating that respondent would choose to keep fishing, despite tax T	0.8066 (0.3950)	0.7905 (0.4073)
E	Likert-scale subjective ex post assessment of current environmental quality at site	-	8.073 (2.177)

Table 2

Parameter Estimates for "Basic" and "Environmental" Models

Parameter	Basic Model	Environmental Model
β_1 (z)	1.381 (1.080)	1.218 (0.6385)
β_2 (q)	0.1109 (6.635)	0.04825 (1.051)
/s3 $(z^2/2)$	0.6173 (1.526)	1.081 (1.106)
β_4 (zq)	0.008387 (1.990)	0.006219 (0.6773)
β_5 $(q^2/2)$	-0.008041 (-8.611)	-0.0037s5 (-1.383)
γ_1 (zE)	-	0.0780S (0.4168)
γ_2 (qE)	-	0.007991 (1.389)
γ_3 $(z^2E/2)$	-	-0.07346 (-0.6631)
γ_4 (zqE)	-	0.0003104 (0.1882)
γ_5 $(q^2E/2)$	-	-0.0005533 (-1.664)
ν[a]	15.13 (31.79)	15.15 (31.76)
P	0.2929 (4.631)	0.2975 (4.637)
Log L	-2339.80	-2334.69

[a] See Cameron (1988a) for discussion of additional parameters.

Table. 3

Properties of the Fitted Utility Function

Property	E - 10	E - 8.0731	E - 6
Utility Function Parameters:			
β_1*	1.998	1.848	1.686
β_2*	0.1282	0.1128	0.09619
β_3*	0.3467	0.4883	0.6406
β_4*	0.009326	0.008726	0.008082
β_5*	-0.009288	-0,008222	-0.007075
Function Saddle Point:			
z*	-5.973	-3.954	-2.764
q*	7.802	9.518	10.44
Demand Elasticity wrt			
price	-0.06034	-0.07351	-0.09211
income	0.1623	0.1610	0.1593
Compensating Variation for Complete Loss of Access	$3742	$2970	$2283
Equivalent Variation for Complete Loss of Access	$3741	$2997	$2316
EV for Access Restricted to a of Current Fitted Level, for a -			
0.1	$3018	$2418	$1867
0.2	2376	1903	1470
0.3	1814	1453	1122
0.4	1329	1064	823
0.5	921	737	570
0.6	588	471	364
0.7	330	265	205
0.8	147	117	91
0.9	37	29	23

10,22. The 5% critical value for a $X^2(5)$ distribution is 11.07 and the 10% critical value is 9.24. Thus , the improvement in the log-likelihood just misses being statistically significant at the 5% level for this small sample. Nevertheless, this difference seems large enough to warrant pursuing the implications of the fitted model. In any case, we can be confident that the statistical significance would improve with larger samples.

5. **Implications of Fitted Parameter Estimates**

In the earlier paper, several properties of the estimated models were recommended for attention. Here, the properties of the fitted utility function vary across levels of environmental quality, E. Consequently, we will evaluate the function at the subsample mean of E (8.0731) ●s well ●s ●t the maximum value of E (10) and at a lower benchmark value (6), which represents approximately one standard deviation below the mean. It is entirely possible to compute values for several Interesting quantities *for* each individual In the sample. Here, however, we will focus on the "mean" consumer. Note that we have ●lected to use the mean values for income and fishing day expenses computed for the entire sample of 3366, on the presumption that the means in this sample are more typical of the mean for the population ●s ●whole. (This is arbitrary; the results will be similar for the "mean" consume in the smeller subset.)

Table 3 summarizes several properties of the fitted utility function for the three benchmark levels of environmental quality. As expected, decreases in ●swlromental quality substantially affect the value respondents place on access to this fishery. Value in this case is measured several ways. Compensating variation is the amount of additional income ●respondent would require, if denied access to the resource, to make their utility level the seine ●s that which could be achieved with the optimal level of access.

Table 5

Descriptive Statistics for E Variable

MOMENTS

N	506		
MEAN	0.07312	SUM	4085
STD DEV	2.17742	VARIANCE	4.74118
SKEWNESS	-1.216	KURTOSIS	0.897612

QUANTILES(DEF=$)

1009 MAX	10	98%	10
75% Q3	10	95%	10
508 MED	9	90%	10
25% Q1	7	10%	5
0% MIN	1	5%	4
		1%	1

RANGE	9
Q3-Q1	3
MODE	10

Table 6

Frequency Distribution of E Values

		FREQ	CUM. FREQ	PERCENT	CUM. PERCENT
1	]*	7	7	1.38	1.38
2	]*	7	14	1.38	2.77
3	]**	10	24	1.98	4.74
4	]**	11	35	2.17	6.92
5	]*********	46	81	9.09	16.01
6	]*****	25	106	4.94	20.95
7	]********	41	147	8.10	29.05
8	]*******************	93	240	18.38	47.43
9	]****************	81	321	16.01	63.44
10	]*************************************	185	506	36.56	100.00

```
----+--+--+- ---+---+---+---+---+---+-
   20 40 60 80 100 120 140 160 180
```

FREQUENCY

Equivalent variation is the loss of income which would leave the respondent just as much worse off as would a denial of access. We also compute the equivalent variation for incomplete reductions in the level of access.

A visual depiction of the effect of environmental quality on the preferences of anglers (defined over fishing days and all other goods) is provided in Figure 1 for E - 10 (which can be considered "good" environmental quality) and for E - 6 ("relatively poor" environmental quality). As anticipated, indifference curves for E = 10 have considerably greater curvature, implying that anglers are less willing to trade off fishing days for other goods when the environmental quality is high. In contrast, with poorer environmental quality, the curvature is considerably less, implying that under these circumstances, anglers consider other goods to be relatively better substitutes for fishing days. For example, when E = 6, the same change in the relative price of ● fishing day will lead to ● larger decrease in the optimal number of days consumed than when E = 10.

In a ddition to the properties of the utility function and its corresponding Marshallian demand functions, we might be interested in calculating the derivatives of these Marshallian demand functions with respect to the level of the E variable. The Marshallian demand function for the model with heterogeneity is:

(2) $$q = [(\beta_2+\gamma_2 E) + (\beta_4+\gamma_4 E)Y - (\beta_1+\gamma_1 E)F - (\beta_3+\gamma_3 E)FY] \ / \ [2(\beta_4+\gamma_4 E)F - (\beta_3+\gamma_3 E) F^2 - (\beta_5+\gamma_5 E)]$$

Table 4 gives the utility maximizing number of fishing days demanded at the sample mean values of F and Y, ●s ● function of the subjective level of environmental quality, E. Locally, there ●re only very slight differences in these fitted demands as ● consequence of e nvironmental changes.

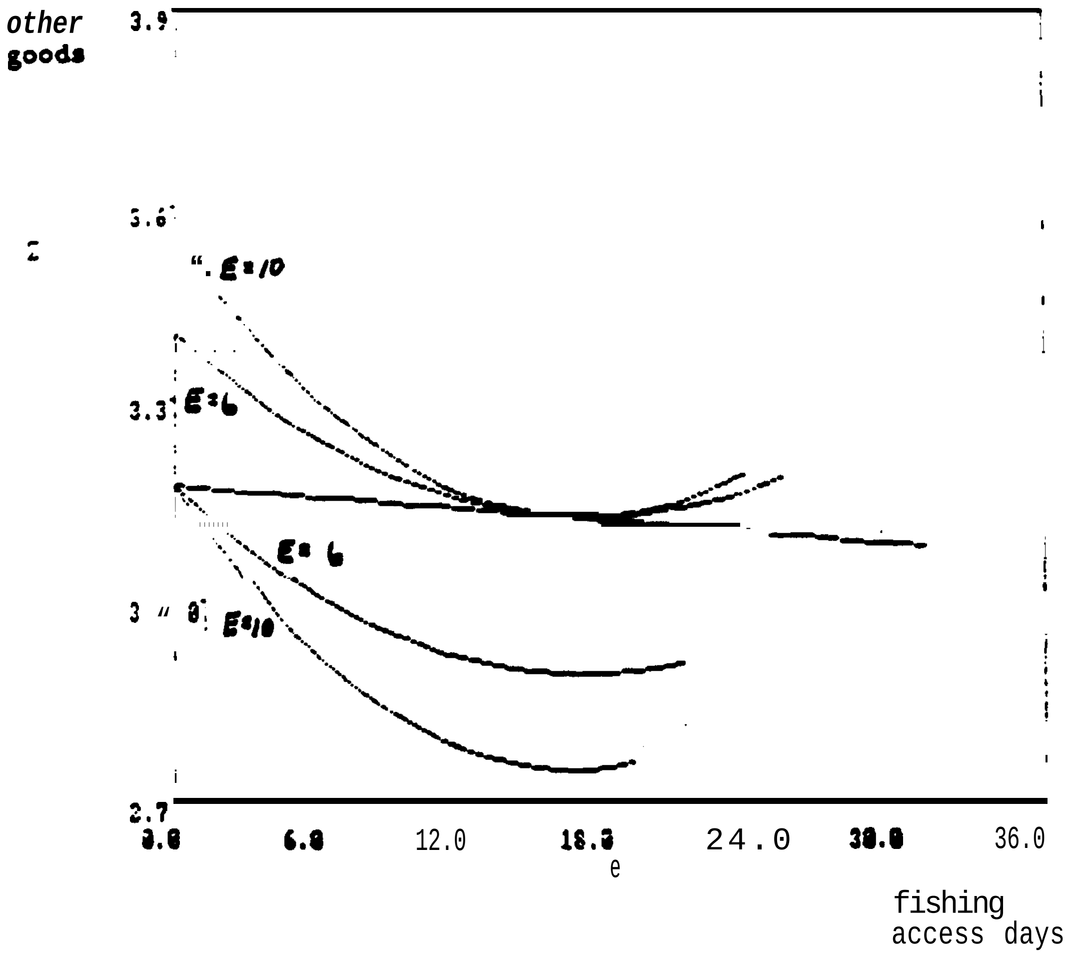

Figure 1. Fitted indifference curves for consumer with mean characteristics and E - 10; ● an for E - 6

direct effects of changes in pollution levels- -by imposing counterfactual changes in the quantities of pollutants and recomputing the fitted individual valuations; and (b.) *indirect* effects of changes in pollution levels--for example, by imposing predicted changes in catch rates and recomputing individual valuations. The difference in the population weighted sums of these individual valuations before and after the simulated reductions in pollution levels is a measure of the social benefit of the' hypothesized clean-up program. This overall change in social value can be added *to* estimates of other relevant benefits (i.e. for market activities) and the total can be compared to the costs of the program in order to determine its economic advisability.

For our Texas fishery, there is some concern at present about the proposed widening and deepening of the Houston Ship Channel, which is anticipated to have a substantial negative environmental impact. If statistically discernible effects of water quality upon the value of this recreational fishery can be found, our fitted models can simulate the changes in value resulting from changes In water quality due to projects such as this.

Section 2 of this paper reviews the intuition and the details of the statistical model which we will us. to fit valuation functions. Section 3 outlines the data. Section 4 considers “naive” specifications of the “valuation function” and ● xplains how implied demand functions can be extracted from the estimated models. Section 5 presents some preliminary empirical results. Section 6 digresses to evaluate the determinants ***of*** catch success, an issue which is important to our ability to assume erogeneity of the explanatory variables in the valuation function. Section 7 “examines respondents' claimed motivations for going fishing and their subsequent satisfaction levels, issues which are fundamental to the form of the basic utility functions which underlie the demand for fishing days. Section 8 takes advantage of explicit questions regarding perceived pollution levels to address whether pollution levels enter directly or indirectly into people's utility functions. We conclude with some tentative findings and a preliminary set of recommendations for improving subsequent surveys which might be used to assess the effects of water quality on the non-market value of recreational fishing.

2. Censored Logistic Regression Models for Referendum Valuation Data

Before addressing this specific empirical project, it is helpful to outline the econometric estimation procedure which will be used to calibrate our model of valuation for this fishery. In Cameron and James (1987), and in a forthcoming paper (Cameron, 1988) I have made the argument that initial estimates of utility-theoretic models of valuation in the spirit of Hanemann (1984) (or even entirely data-driven *ad hoc* valuation models) using referendum data can be obtained quite simply using packaged logit or probit maximum likelihood algorithms. Since the numbers of observations in the models explored in this study are large, and since the specifications involve a wide array of potential explanatory variables, I opt here to perform initial estimations using censored logistic regression models. The computations necessary to optimize the likelihood function underlying these models does noc involve myriad evaluations of the non-closed-form integral for the cumulative normal density function. The optimization is faster and cheaper than it would be for a censored normal regression model. Furthermore, since the parameters of the censored logistic regression modal can be solved-for from the parameter estimates produced by conventional packaged maximum likelihood logit models, and the SAS computer package provides ML logit routines in its MLOGIT module, we find it expedient to pursue initial trial specifications in the context of che SAS package. This also allows us to take advantage of the superior data-manipulation capabilities of this program.

Based my earlier studies, the implicit valuation function parameter estimates produced by either the censored normal (probit-type) or censored logistic (logit-type) estimation procedures are very similar. The slight differences in the shape of the conditional density function for the regression errors makes only modest differences in the fitted values of the ultimate "regression" model. Hence it is safe to presume that explanatory variables which make a statistically significant contribution to the valuation function in the context of a simple logit specification will also be important under alternative distributional hypotheses.

2.1 *Reviw of Censored Regression Models for Referendum Data*

Since the censored logistic model is not yet in the public domain, I will briefly reproduce the derivation of the model.

"Referendum" surveys have recently become very popular as a technique for eliciting the value of public goods or non-market resources. Numerous applications of these methods now exist. (For comprehensive assessments of these survey instruments and detailed citations to the seminal works and specific applications, the reader is referred either to Cummings, Brookshire, and Schulz. (1986), or to Mitchell and Carson (1988).

The referendum approach first establishes the attributes of the public good or the resource, and then asks the respondent whether or not they would pay or accept • single specific sum for access. (It is crucial that the arbitrarily assigned sums be varied across respondents.) This questioning strategy is attractive because it generates a scenario for each consumer which is similar to that encountered in day-to-day market transactions. A hypothetical price is stated and the respondent merely decides whether to "cake it or leave it." This is less stressful for the respondent than requiring that a specific value be named, and circumvents much of the potential for strategic response bias. The challenge for estimation arises only because the respondent's true valuation is an unobserved random variable. We must infer its magnitude through an indicator variable (the consumer's "yes/no" response to the offered threshold sum) that tells us whether this underlying value is greater or less than the offered value.

In formulating appropriate econometric methodologies for analyzing these data, it is important to begin by imagining how valuation might be modeled if we could somehow readily elicit from each respondent their true valuation. If valuation could be measured like other variables (i.e. continuously), we would simply regress it on all the things that we suspect might affect its level. The econometrically interesting complication with referendum data arises from the fact that we don't know the exact magnitude of the individual's valuation; we only know whether it is greater than or less than some specified amount.

2.2 ***Log-likelihood Function for Censored Logistic Regression***

Referendum data are ***not*** discrete choice data in the conventional sense (see McFadden, 1976, or Maddala, 1983). The procedure developed below is based upon the premise that if we could measure valuation exactly, we would use it explicitly in a regression-type model. [1] The censoring of valuation to be "greater than or less than" a known threshold is a mere statistical inconvenience to be worked around.

[1] Here, we would be using it' explicitly in a "non-normal" regression model, namely, a regression model incorporating a two-parameter logistic density function. But that would be nothing special--econometric researchers have for several years been using maximum likelihood methods to explore Poisson regression, Weibull regression, and a host of ocher distributional assumptions as alternatives to the familiar normal model.

Assume that the unobserved continuous dependent variable is the respondent's true willingness-to-pay (WTP)[2] for the resource or public good, Y_{i}, We can assume that the underlying distribution of Y_i, conditional on a vector of explanatory variables, x_i (with elements j-l,. . . ,P), has a logistic (rather than a normal) distribution, with a mean of $g(x_i,\beta) = x_i'\beta$.

In the standard maximum likelihood binary logit model, we would assume that:

(1) $$Yi - x_i'\beta + u_i$$

where Y_i is unobserved, but is manifested through the discrete indicator variable, I_i, such that:

(2) $$\begin{aligned} I_i &= 1 \text{ if } Y_i > 0 \\ &- 0 \text{ otherwise.} \end{aligned}$$

If we assume that u_i is distributed according to a logistic distribution with mean O and standard deviation b (and with alternative parameter $\kappa - b\surd 3/\pi$, see Hastings and Peacock (1975)), then

(3) $$\begin{aligned} Pr(I_i - 1) - Pr\ (Y_i > 0) - Pr(u_i &> -x_i'\beta) \\ &= Pr(u_i/\kappa > -x_i'\beta/\kappa) \\ &- 1 - Pr(\psi_i < -x_i'\gamma), \end{aligned}$$

where 7 = β/κ●nd we use ψ to signify the standard logistic random variable with mean O and standard deviation b = $\pi/\surd 3$. The formula for the cumulative density up to z for the standard logistic distribution is

(4) $$F(z) = 1 - (1 + \exp[z])^{-1}.$$

---

[2] These models can be adapted very simply to accommodate willingness-to-accept (WTA).

Therefore the log-likelihood function can be written as:

(5) $$\log L = \Sigma - I_i \log(1 + \exp[-x_i'\gamma]) + (1 - I_i) \log \exp[-x_i'\gamma]/(1 + \exp[-x_i'\gamma])).$$

Simplification yields:

(6) $$\log L = \Sigma\, (1 - I_i)(-x_i'\gamma) - \log[1 + \exp(-x_i'\gamma)].$$

It is not possible in this model to estimate β and κ separately, since they appear everywhere as β/κ. The model must therefore be evaluated in terms of its estimated probabilities, since the underlying valuation function, $x_i'\beta$, cannot be recovered.

With referendum data, however, each individual is confronted with a threshold value, t_i. Earlier researchers have included t_i as one of the x_i variables in the conventional logit modsl described above. In our new model, we conclude by the respondent's (yes/no) response that his true WTP is either greater than or less than t_i. We can assume a valuation function' as in (1) with the same distribution for u_i, but we can now make use of the variable threshold value t_i as follows-- in a new model which might be described as special form of "censored logistic regression":

(7) $$I_i = 1 \text{ if } Y_i > t_i$$
$$= 0 \text{ otherwise,}$$

so that

---

[3] Note that many textbooks (e.g. Maddala, 1983) exploit the symmetry around zero of the standard logistic distribution to simplify these formulas even further, We simplify this way to preserve consistency with the next model where we estimate k explicitly.

[4] However, it is now straightforward to make the mean of the conditional distribution any arbitrary function $g(x_i,\beta)$.

(8) $$\Pr(I_i - 1) - \Pr(Y_i > t,) - \Pr(u_i > t_i - \mathbf{x}_i'\beta)$$
$$- \Pr(u_i/\kappa > (t_i - \mathbf{x}_i'\beta)/\kappa)$$
$$- 1 - \Pr(\psi_i < (t_i - \mathbf{x}_i'\beta)/\kappa).$$

With this modification, the log likelihood function can now be written as:

(9) $$\log L = \Sigma - I_i \log(1 + \exp[(t_i - \mathbf{x}_i'\beta)/\kappa])$$
$$+ (1 - I_i) \log(\exp[(t_i - \mathbf{x}_i'\beta)/\kappa]/(1 + \exp[(t_i - \mathbf{x}_i'\beta)/\kappa])).$$

As before, this can be simplified to yield:

(lo) $$\log L - \Sigma (1 - I_i)[(t_i - \mathbf{x}_i'\beta)/\kappa] - \log(1 + \exp[(t_i - \mathbf{x}_i'\beta)/\kappa]).$$

The presence of t_i allows κ to be identified, which then allows us to isolate β so that the underlying fitted valuation function can be determined. Note that if t_i - 0 for all i, (10) collapses to" the conventional logit likelihood function in (6).

The log-likelihood function in (10) can be optimized directly using the iterative algorithms of • general nonlinear function optimization computer program[s] and this is undeniably the preferred strategy when the option is readily available. There exist function optimization algorithms which will find the optimal parameter values using only the function itself (and numeric derivatives) . Howover analytic first (and second) derivatives can sometimes reduce computational costs considerably. See Appendix I for a description of

[s] We used a program called GQOPT - A Package for Numerical Optimization of Functions, developed by Richard E. Quandt and Stephen Goldfeld at Princeton University (Department of Economics). Roughly optimal parameter values are first achieved using the DFP (Davidon-Fletcher-Powell) algorithm; these values are then used as starting values for the GRADX (quadratic hill-climbing) algorithm to achieve refined estimates (i.e. to a function accuracy of 10^{-10}). We understand that, the programs GAUSS and LIMDEP can also be adapted to optimize arbitrary functions.

the gradient and Hessian components helpful in nonlinear optimization of this log-likelihood function.

Maximization of the log-likelihood function in (10) will yield separate estimates of β and κ (and their individual asymptotic standard errors). However, estimates of $-1/\kappa$ and β/κ can, in the case of $g(x_i,\beta) - x_i'\beta$, be obtained quite conveniently from conventional maximum likelihood "packaged" logit algorithms, although we emphasize that this is merely a handy "short-cut" to be used if a general function-optimization program is not available. If we simply include the threshold, it, among the "explanatory" variables in an ordinary (maximum likelihood) logit model (as has typically been done by earlier researchers 'using referendum data), it is easy to see that:

(11) $$-(t, x') \begin{bmatrix} -1/s \\ \beta/\kappa \end{bmatrix} = -x^{*\prime}\gamma^{*},$$

The augmented vectors of variables, x* and coefficients, Y*, may be treated as one would treat the explanatory variables and coefficients in an ordinary logit estimation. From 7*, it is possible to compute point estimates of the desired parameters β and κ. If we distinguish the elements of 7* as (a, 7) - $(-1/\kappa, \beta/\kappa)$ then $\kappa = -1/a$ and $\beta_j = -\gamma_j/\alpha$, j - 1,. ..,p. However, accurate asymptotic standard errors for these functions of the estimated parameters are not produced automatically. If the conventional logit algorithm used allows one to savo the point estimates and the variance-covariance matrix estimates for subsequent calculations, there are some alternative, relatively simple, methods for calculating approximate standard errors using only the information gleaned from a conventional logit model. (See the second portion of Appendix ~.)

3. Data

The Texas Parks and Wildlife Coastal Fisheries Branch has conducted a major creel survey of recreational fishermen from the Mexican border to the Louisiana state line during the period of May to November, 1987. The survey records detailed catch information, and appends a list of "socioeconomic" questions which make up the contingent valuation portion of questionnaire. Over 10,000 responses were collected; our admissibility criteria reduce the usable sample to 5526, which is still a very large number of responses. Hydrological data are collected simultaneously at each investigation site along with the CV investigation. We merge these survey data with an assortment of data drawn from other sources, notably the Texas Department of Water resources and the 1980 Census. Extensive documentary information on variable construction is contained in Appendix II. The reader is referred to that section for details.

4. Specifications

4.1 ***"Naive" Models***

As always, the very simplest model of fisheries valuation could presume that we only wish to know the marginal mean of the value of a year's fishing. If we include only the offered threshold as an explanatory variable in a logit model to explain the yes/no response, the fitted model will yield the marginal mean and marginal standard deviation of values (ignoring heterogeneity among respondents). This number is valuable if we can safely assume that the interview sample is a truly random sample of the "use" population, and if we know the size of the sample relative to the entire population. Under these limited circumstances, we can extrapolate from these per-person estimates to the total fitted "use" value of the fishery at the time of the survey and under the current conditions of the fishing population and the resource itself.

If we were not concerned with forecasting the effects of changes in the fishing population or changes in resource attributes, this single point estimate and its standard deviation would tell us most of what we need to know. However, resource valuation models can be extremely useful for forecasting the anticipated effects upon resource values of changes in resource attributes. In this study, we are primarily concerned with changes in species abundance and changes in water quality. We will control for cross-sectional heterogeneity in anglers and in resource attributes. Having calibrated a model acknowledging this heterogeneity, we will have a fitted model which will be useful for predicting the effects on the value of the resource of • wide range of policy-induced changes in our explanatory variables.

Where resource values are sensitive to water quality "parameters," we can determine the effect of a change in the level of each parameter on the social resource value of the resource. Comparing the social benefits of pollution control, for example, with the social costs of a cleanup program can provide a useful assessment of the economic efficiency implicationns of cleanup proposals. If resource values are sensitive to species abundance or size (either overall or by individual species), there will be important implications for fisheries management. Likewise, if access values are sensitive to the day of the week interacted with respondent characteristics, these valuation models could indicate how fishing licenses and closures could be decided in order to optimize both the resource base and the aggregate social value of access.

One initial problem observed in the data concerns the distinction between willingness to pay and actual ability to pay. "Demand" in the economic sense might be limited to "effective" demand, not just wishful thinking. This distinction is unresolved at present, but must be addressed at some point during this study.

The reason for raising this issue is that we observe in our sample that many of the people who claim to be willing to pay S20000 to continue fishing over the year come from zip codes where $20000 exceeds the median household income. While it may be that the respondent's household income is substantially larger than their zip code median, these responses cast some doubt on the accuracy of "effective" demands implied by responses to the $20000 referendum value. Fortunately, however, we have a very large sample, by contingent valuation standards. The referendum threshold values were assigned randomly to different respondents. Therefore, we will lose little except some estimation efficiency by dropping all respondents who were offered this extremely high threshold. It is quite possible that many of the respondents who respond that they would be willing to pay $20000 for a year's access co the recreational fishery are responding strategically, rather than realistically. Strategic biases from these responses can be quite high, so the results reported here exclude the $20000 offers, regardless of their yes or no response. (Current plans for the continuation of the survey call for this threshold to be dropped anyway. All specifications will eventually be estimated with the ***full*** sample, with $20000 threshold respondents deleted, and with thresholds exceeding $500, 2000, and $1500 deleted. This allows us to assess the sensitivity of the valuation function parameter estimates to survey design.)

4.2. Derivation *of "Demand Functions" Underlying the Valuation Data*

In this survey, the underlying continuous dependent variable Y is the respondent's total valuation of a full year's access to the fishery, which we will designate as "total willingness to pay," TWTP. We can still estimate models for TWTP using censored logistic (or censored normal) regression implicitly via an ordinary MLE logit (or probit) algorithm. We can manipulate the estimated discrete choice. coefficients to uncover the individual coefficients (β) for any arbitrary underlying linear-in-parameters fitted total TWTP relationship, $x_1'\beta$. However, the TWTP function must then be solved to yield the corresponding implicit demand function.

To illustrate, suppose that our ●xplanatory variables included only the number of fishing days per year, q, and other shift variables which we will denote by the "generic" variable X. Then the fitted quantity log(TWTP) will be $\beta_1 + \beta_2 \log(q) + \beta_3 X$, where the parameters are now their estimated values and we ignore the stochastic component. The price willingly paid for a year's access is the total amount willingly paid for all trips. To determine the marginal WTP for one additional trip, we need to find the expression for the derivative: $\partial TWTP/\partial q$. Since dlogTWTP/slog(q) is just β_2, $\partial TWTP/\partial q$ can be assumed to be β_2 times the ratio of fitted $TWTP$ ($= \exp[\beta_1 + \beta_2 \log(q) + \beta_3 x]$) to q. (To be strictly correct in treating this exponentialted fitted value of log(TWTP) as the fitted conditional mean of TWTP, we would scale this quantity by $\Gamma(1+\kappa)\Gamma(1-\kappa)$, but this term affects only the intercept of the resulting demand expression, so will will suppress it for simplicity of exposition.) If we consider $\partial TWTP/\partial q$ to be p(q), the presumed demand relationship can be expressed as:

$$\text{(12)} \qquad \log p(q) - \log \beta_2 - \log(q) + \beta_1 + \beta_2 \log(q) + \beta_3 X.$$
$$- (\beta_1 + \log \beta_2 + \beta_3 X) + (\beta_2 - 1) \log(q)$$

We can rearrange these formulas to isolate log(q) on the left-hand side:

$$\text{(13)} \qquad \log(q) - [(\beta_1 + \log(\beta_2))/(1-\beta_2)] - [1/(1-/32)] \log p(q)$$
$$+ [\beta_3/(1-\beta_2)] \, x$$
$$- al^* + \alpha_2^* \log p(q) + a_3^* X.$$

We have thus arrived at *point estimates* for the implicit demand function corresponding to a log-log functional form for TWTP. The coefficients on log(p) have the straightforward interpretation of price elasticities of demand for fishing trips. If the X variables contain the logarithm of income, then the corresponding coefficient in the α_3^* vector gives the income elasticity of demand. Other variables making up the X vector will include respondent and resource attributes which shift the demand function.

Of course, the β parameters in the above formulas are transformations of the original MLE logit parameters. It will certainly ba possible to "automate" the computation *of* all of the a* parameters of the implied demand function if we use software which allows us to save the fitted logit parameters to be used in subsequent computations (e.g. SHAZAM). Our initial exploratory models focus on the estimation of the β parameters, indirectly via the ordinary MLE logit ●pproach. However, once promising specifications have been identified, and if one is willing (and able) to estimate a censored regression log-likelihood function directly, using non-linear optimization algorithms, it would be straightfo~ard to reparameterize the censored regression likelihood function described above so that the elasticity parameter α_2^* and the other α_3^* parameters could be estimated directly. Note that $\beta_1 = -\log[\alpha_2^*/(1+\alpha_2^*)] - \alpha_1^*/\alpha_2^*$ (Plus an additional term in Γ functions of κ) and β_2 - $(1+\alpha_2*)/\alpha_2*$ and β_3 - $-\alpha_3*/\alpha_2*$. The expression $x_i'\beta$ in the likelihood function should therefore be replaced by:

(14) $$g(x_i,\beta) - - \log[\alpha_2*/(1+\alpha_2*)] - \alpha_1*/\alpha_2* + (1+\alpha_2*)/\alpha_2* \log(q_i) + (-\alpha_3*/\alpha_2*) X - g(\alpha_1*,\alpha_2*,\alpha_3*,q_i,X_i).$$

The log-likelihood function to be optimized will now be:

(15) $$\log L = \Sigma (1 - I_i)[(t_i - g(\alpha_1*,\alpha_2*,\alpha_3*,q_i,X_i))/\kappa] - \log(1 + \exp[(t_i - g(\alpha_1*,\alpha_2*,\alpha_3*,q_i,X_i))/\kappa]).$$

Since the individual parameters al*, α_2*, and α_3* are fully identified, the nonlinear function optimizing program will produce the desired results. (The analytical gradient and Hessian formulas will be different and much more complicated, but •s noted, many programs will compute their own numeric derivatives.) This model would produce not only direct point estimates of the demeand elasticities, α_2*, and the other demand function derivatives, but also their directly estimated asymptotic standard errors. By the invariance property of maximum likelihood, the point astimates should be identical, so extremely accurate starting values for these nonlinear algorithms can be generated by transforming the ordinary logit point estimates. The nonlinear optimization of the likelihood function in (15), however, will yield asymptotic standard error estimates (and therefore t-ratios for hypothesis testing) which could only be approximated with considerable difficulty from the asymptotic variance-covariance matrix produced automatically for the ordinary logit parameter estimates.

5. Preliminary Empirical Results

5.1 *Unspecified Geographic Heterogeneity in Demand*

If we assume geographic homogeneity to begin with and estimate a TWTP model in log *form* simply as a function of the log of the total number of fishing trips (LTRIPS). the log of median zip code household income (LINC), and market expenditures (MON), we get the ordinary logit point estimates in Table la. To determine whether there exists systematic geographical variation in the demand function for fishing days, we then extend this model to include a set of qualitative dummy variables, one for each major bay system: .

MJl - Sabine-Neches
MJ2 - Trinity-San Jacinto (Galveston Bay)
MJ3 - Lavaca-Tres Palacios (Matagorda Bay)
MJ4 - San Antonio-Espiritu Santo
MJ5 - Mission-Aransas
MJ6 - Corpus Christi-Neuces
MJ7 - Upper Laguna Madre
MJ8 - Lower Laguna Madre

Since the Galveston Bay area accounts for Houston, we arbitrarily make MJ2 the omitted category when we enter sets of major bay dummy variables. Coefficients on the other dummies therefore represent shifts in the dependent variable relative to the values for MJ2.

Individually, several of these dummy variables are statistically significant. Collectively, a likelihood ratio test for the incremental contribution of the complete set of dummy variables indicates that geographical variation in demand is statistically significant at the 10% level.

If we take the ordinary logit parimeter estimates from Table lb and transform them to yield the parameters of the log-log demand function corresponding to this TWTP function (shown in the last column of Table lb), we find that the price elasticity of demand for a fishing day, controlling for qualitative geographical variation via the set of major bay dummy variables,

Table 1a

Extremely Simple Model: Geographic Homogeneity of Demand

Variable	Est. Coeff.	Asy. t-ratio
LOFFER	-0.5608	-24.631
LTRIPS	0.3077	12.05
LINC	0.2488	2.316
MON	0.001734	6.167
constant	1.718	1.625

max LogL - -2550.6.

Table lb

Augmented Simple Model: with Geographic Heterogeneity (dummies)

Variable	Est. Coeff.	Asy. t-ratio	Demand f^n q
LOFFER	-0.5638	-24.68	
LTRIPS	0.3095	12.08	-
LINC	0.1278	1.058	0.5024
MON	0.001801	6.234	0.0071
MJ1	-0.1827	-0.7526	-0.7185
MJ3	-0.2589	-1.796	-1.018
MJ4	-0.03043	-0.1706	-0.1197
MJ5	-0.1167	-0.9230	-0.4587
MJ6	-0.3405.	-2.819	-1.339
MJ7	-0.2878	-2.149	-1.131
MJ8	-0.3184	-2,478	-1.252
cons tant	3.119	2.563	-
log(p)	-	-	-2.217

max LogL - -2S44.2 (LR test statistic for the set of seven major bay dummy variables is 12.8. X^2(.05) critlcal value - 14.07; X^2(.10) critical value - 12.01.

is -2.217. The income elasticity of demand is 0.5024. the change in the log of fishing days for a one dollar increase in market expenditures is 0.0071. The seven bay dummies shift the log of fishing days by -0.72, -1.02, -0.12, -0.46, -1.34, -1.13, and -1.25, respectively.

5.2 *Quantifying Geographical Heterogeneidy in Demand*

The evidence therefore suggests that geographical variation exists in the demand function for recreational fishing days in Texas. But in the model in the last section, the reasons for this geographical variation are non-*specific.* Demand could differ by bay system for a variety of reasons. First, systematically different types of people, with different preferences or constraints, might be utilizing each different bay system. (This is suggested by the drop in significance of the LINC variable when bay dummies are included.) The quality attributes of the resource could also vary across bay systems. If fish abundance affects TWTP, then variations in species abundance across bays could be captured by these dummy variables. If fishing conditions (weather and water conditions) vary systematically across bays, this effect could also be manifested in the dummy coefficients. In particular, however, we are curious to see whether measurable variations in water quality "parameters" exert any statistically discernible influence on TWTP, In lieu of a set of simple bay dummy variables, then, we begin to consider specifications employing variables which quantify the inter-bay differences in resource attributes.

Table 2a augments the model in Table la by including • variable, TOTAL, for the total number of fish actually caught on the interview day. (In subsequent models, we will consider exogenous measures of abundance for individual species, by month and bay.) TOTAL current catch is not statistically significant, but it bears the anticipated sign, so we will

Table 2a

Simple Model with Current Total Catch, No Water Quality

Variable	Est. Coeff.	Asy. t-ratio
LOFFER	-0.5617	-24.64
LTRIPS	0.3064	11.99
LINC	0.2504	2.331
MON	0.001735	6.156
TOTAL	0.003109	1.090
constant	1.718	1.625

max LogL - -2549.9.

Table 2b

Augmented Model: Geographic Heterogeneity in Water Quality

Variable	Est. Coeff.	Asy. t-ratio	Demand f^n q
LQFFER	-0.5637	-24.63	
LTRIPS	0.3132	12.19	-
LINC	0.2299	1.888	0.9177
MON	0.001675	5.953	0.00669
TOTAL	0,003603	1.243	0.01438
REsu	0.005401	2.138	0.02156
PHos	1.076	2.685	4.296
CHLORA	0.02313	2.725	0.09233
LOSSIGN	0.005420	1.359	0.02163
CHROMB	-0.009027	-0.969	-0.03603
LEADB	-0.006231	-1.160	-0.02487
CONSTANT	3.119	2.563	-
log(p)	-	-	-2.250

max LogL - -2536.9 (LR test statistic for the set of six water quality variables Is 26.0. $X^2(.05)$ critical value - 12.59.

retain it in the model as a rudimentary control for "catch success." TOTAL will vary with individual fishing skill or effort, but it will also vary across major bays as species abundance varies. Of primary interest for the purposes of this study, of course, is the potential influence of water quality measures on TWTP, and hence on the demand function for recreational fishing days.

Our supplementary data from the Texas Department of Water Resources provides sufficient sample on several common water quality parameters to allow us to generate monthly averages for each bay system. For others, however, the limited number of samples only allows reliable estimates of annual averages for each bay system. (This is particularly true for metals found in bottom deposits. We are awaiting further supplementary data on bottom deposits from the shellfish division of the Health Department.) In our first pass through the data, we examined pairwise correlations between species abundance and a wide range of water quality measures and selected several which seemed to have an obvious relationship to species abundance. (We have tangentially explored regressions of actual catch and monthly abundance of each species on all reliably measured water quality attributes, described in Section 6.)

To illustrate the potential for water quality to affect TWTP for fishery access, we display in Table 2a some preliminary results for a rudimentary model incorporating ●selection of water quality variables. (We emphasize that this model is by no means our last word on the subject. We have barely "scratched the surface" of a wide variety of potential specifications.)

The water quality variables we include in Table 2b which ●re available as monthly averages for each bay system are RESU (total non-filterable residue, dried at 105C, in mg/1), PHOS (phosphorous, total, wet method, mg/1 as P), and CHLORA (chlorophyll-A, $\mu g/l$, spectrophotometric acid method).

Variables which can at present only be used as annual averages for each bay system are LOSSIGN (loss on ignition, bottom deposits, scaled to g/kg), CHROMB (chromium, total, in bottom deposits, mg/kg, dry weight), and LEADB (lead, total, in bottom deposits, mg/kg as PB dry weight).

Transforming the ordinary logit parameter point estimates in Table 2b according to the formulas suggested above for solving such a model for the corresponding log-log demand function yield the demand parameters given in the last column of Table 2b. The price elasticity of demand for fishing days is now -2.250. The income elasticity of demand is now 0.9177, (The increase is probably attributable to the fact that we are not longer implicitly controlling for geographic income variation via the set ofmajor bay dummy variables, so that this measure is probably more reliable.) A one dollar increase in market expenditures corresponds to a 0.0067 increase in the log of the number of fishing days demanded, suggesting that market goods associated with the fishing day (if typical) are complementary goods. An extra fish caught on the interview day affects demand by increasing the log of days demanded by 0.0144. Demand is higher where non-filterable residues are higher, where phosphorous concentrations are higher, where loss on ignition is greater, and where there are greater concentrations of chlorophyll-A. However, the presence of metals in bottom deposits, such as chromium and lead, corresponds to lesser demand for fishing days.

5.3 *Controlling for Demographic Heterogeneity Among Respondents*

Having determined that there will be some water quality measures which appear to have a statistically significant impact upon the value of access to this recreational fishery, we now introduce three variables designed to control for interregional variations in demographics. We use PSPNOENG, PVIETNAM, and PURBAN. To the extent that the demographic characteristics of anglers are correlated with the water quality in the areas where they fish, it will be important to allow for demographic effects in any attempt to identify the distinct effects on resource values of water quality measures.

'Table 3 gives the ordinary MLE logit parameter estimates with these additional explanatory variables. The last column of the table gives the point estimates of the parameters of the corresponding log-log demand function (and its shift variables). None of these three variables make statistically significant contributions to explaining resource values, but this may be an artifact of collinearity among the variables, so we retain them out of interest in determining point estimates of their effects on the demand functions The proportion of unassimilated Hispanic residents in the respondent's zip code (PSPNOENG) tends to decrease the log of fishing days demanded by about 1.5; the proportion of Vietnamese (PVIETNAM) has a dramatic effect on values (which persists through a variety of alternative specifications)-- this variable increases the log of fishing days demanded by 31.8! People from relatively more urbanized l reas apparently demand fewer fishing days.

5.4 ***Introducing Variations in Species Catch Rates, Species Abundance***

The total number of fish caught on the interview dat has been included as an explanatory variable in several of the specifications discussed above.

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[6] Bear in mind that just because a particular variable is not statistically significantly different from zero for • particular sample of data does not imply that it is zero. We retain variables for which the coefficient estimates are stable • cross alternative specifications. With better data (e.g. with a more equal distribution of "yes" • nd 'no" responses) there might have been enough information in this sample to reduce the sizes of the standard errors. Likewise, the error distribution may have an apparent dispersion larger than the actual dispersion because we are using group averages as proxies for several of our explanatory variables, including income. What could be an excellent "fit" with the true data could be converted to a poorer "fit" by the use of group averages.

Table 3

Augmented Model: Demographic Variables

Variable	Est. Coeff.	Asy. t-ratio	Demand f^{n} q
LOFFER	-0.5637	-24.63	
LTRIPS	0.3132	12.09	-
LINC	0.2281	1.512	0.9068
MON	0.001632	5.731	0.006488
PSPNOENG	-0.3915	-0.5880	-1.556
PVIETNAM	8.000	1.237	31.80
PURBAN	-0.1190	-1.400	-0.4732
TOTAL	0.003624	1.250	0.01441
RESU	0.005333	2.106	0.02120
PHOS	1.142	2.819	4.541
CHLORA	0.02235	2.631	0.08884
LOSSIGN	0.007762	1.686	0.03085
CHROMB	-0.01300	-1.194	-0.05169
LEADB	-0.004626	-0.8354	-0.01839
cons tant	1.404	0.9377	-
log(p)	-		-2.241

max LogL - -2534.9

Given that we have a wealth of data on the catch and on overall abundance, by individual species, it seems worthwhile to experiment with valuation models which discriminate among the effects of individual species on the annual value of access to the fishery.

Perplexing "results emerge as we include variables relating to the catch of individual species. There are seven major species in our working data set: REDS, TROUT, CROAK, SAND, BLACK, SHEEP, and FLOUND (See Appendix II for detailed descriptions). We have experimented with:

a.) actual current day catch rates;
b.) monthly average actual catch rates by bay system;
c.) "annual" average actual catch rates by bay system;
d.) monthly average abundance indexes by bay system from the TPW resource monitoring program;
e.) annual average abundance indexes by bay system from thr TPW resource monitoring program

For all of these measures of catch rates, we "find that for at least some species, often important ones, the coefficients in MLE logit models imply that greater catch rates or greater abundance decreases the value of the resource. This seems highly implausible, and points to the existence of important unmeasured variables, negatively correlated with catch rates, which are positively correlated with resource values and (by their omission) leave the catch rate variables with counterintuitive signs.

Logically, since we are asking respondents to value a year's access to the fishery, it should be expected annual catch which influences their values. But anglers may by myopic. Actual average catch rates or abundance may be discounted in favor of current perceptions of catch rates. A variety of models have been estimated, but for illustration, we report our findings for one which uses monthly bay average catch rates. It 1s our inclination that average catch rates should be preferred to individual current catch rates because the latter does not control for individual expertise or fishing intensity. The monthly averages reflect the catch of the "average" angler, abstracting from individual differences in skill or enthusiasm.

Results for a specification which replaces the TOTAL current catch variable with the full set of monthly catch averages for each bay system are presented in Table 4. The coefficients on MATROUT, MASAND, and MABLACK are negative, and the point estimate for the coefficient on MABLACK is relatively large. The set of catch variables collectively results in an improvement of only 3.0 in the log-likelihood function, which is not sufficient to reject by an LR test the hypothesis that the catch data should be excluded from the model. But perhaps we are not measuring the desired variables correctly.

It is unfortunate that the survey did not collect information from post-trip respondents regarding their target species. If you only ever fish for one particular species, then the abundance if other species will not affect your value of access to the resource. In fact, of other species compete for the seine biological niche as your preferred species, their abundance might detract from your value of the fishery. This angle will need to be explored. At one point, we made the heroic assumption that observed target proportions in each bay and month for pre-interview respondents carry over to the population as a whole (which is tenuous). Including these target proportions directly in a logistic regression model had no discernible effect, however, probably because the information was not specific to individual anglers (a severe errors in variables problem).

Further investigation of the observable (and unobserved) correlates of catch rates is clearly warranted. At the time of this writing, we have not yet uncovered and explanation for these counterintuitive findings. The following section addresses catch rates explicitly, and describes the search

Table 4

Augmented Model: Monthly Average Catch Rates (by bay system)

Variable	Est. Coeff.	Asy. t-ratio	Demand f^n q
LOFFER	-0.5636	-24.62	-
LTRIPS	0.3129	12.09	-
LINC	0.2158	1.432	0.8604
MON	0.001647	5.725	0.006566
PS PNOENG	-0.3705	-0.5479	-1.477
PVIETNAM	7.421	1.142	29.58
PURBAN	-0.1149	-1.343	-0.4580
MAREDS	0.05111	0.4234	0.2037
MATROUT	-0.02823	-0.6157	-0.1125
MACROAK	0.001740	0.05004	0.006935
MAsAND	-0.02808	-0.5756	-0.1119
MABLACK	-0.2094	-0.6973	-0.8346
MASHEEP	0.4165	1.331	1.660
MAFLOUND	0.06694	0.5238	0.2669
RESU	0.006257	2.328	0.02494
PHOS	1.185	2.671	4.723
CHLORA	0.02056	2.244	0.08195
LOSSIGN	0.006621	1.289	0.02639
CHROMB	-0.009143	-0.7001	-0.03645
LEADB	-0.005987	-0.9940	-0.02387
constant	1.5419	1.030	-
log(p)	-	-	-2.247

max LogL = -2532.7

for potential reasons for the results in Table 4 (and similar results for other models not reported in this paper).

6. Actual Current Catch versus Species Abundance. Regression Models

It is not intuitively obvious whether exogenously measured species abundance, or actual catch rates by the respondent, should be the more appropriate determinant of valuation for the fishing season. Unfortunately, it is rarely easy to extract from respondents a reliable (retrospective) total of each species caught over the past year. We only have the current day's catch of each species in our present survey data. But exogenously measured abundance of each species is not necessarily a good predictor of variations in expected catch from the point of view of the individual who is being asked to value a year of access to the fishery. One reason is that Parks and Wildlife Resource Monitoring controlled samples are not "caught" using the same technology available to recreational fishermen. If fish are present, but are not "biting," they may still be swept up in the nets used by the Monitoring Program, Ideally, we would like to know the success rates (for each species) for a "standardized" recreational angler (with given skills and effort level). If we use individual respondents' actual catch rates, unobservable differences in skill will potentially bias the coefficients on the catch rate in the valuation equationa.

To determine what factors affect individual respondents' currant catch rates, we ran a set of ordinary least squares regressions of each respondent's actual catch of each species (REDS, TROUT, CROAK, SAND, BLACK, SHEEP, and FLOUND) against the corresponding monthly and annual abundance indexes for that species, current market expenditures related to the fishing day (MON), specific fishing experience (SITETRIP, the annual number of trips to the site where the respondent was interviewed), non-specific fishing experience

(NSWTRIP, annual trips to other saltwater fishing sites in Texas), and a number of demographic variables. The demographic variables reflect zip code average or median data drawn from the 1980 Census, so they do not necessarily capture *concurrence* demographics, but we will assume they are close. We include PRETIRED (the proportion of people in your zip code who are retired), PSPANISH (the proportion of people of Hispanic origin), PSPNOENG (the proportion speaking Spanish at home and little or no English--unassimilated immigrants) , PVIETNAM (the proportion indicating Vietnamese origin, PURBAN (the proportion living in areas designated as urban), PTEXNATV (the proportion born in Texas --reflecting familiarity with the fishery or the environment), PFFFISH (the proportion working in forestry, fishing, or farming), and HHLDING (median household income).

These variables may affect catch rates for several reasons. First, demographic differences may influence the target species chosen. Alternatively, these variables may serve as proxies for fishing experience or skill . They may also proxy whether or not the objective of the fishing trip is purely recreational, or whether the catch is a significant supplement to the angler's diet. Demographic measures may also covary systematically with geographical regions ●nd therefore with species abundance.

Table A.1 (at the back of this paper) displays the results of the seven OLS regressions. Interestingly, the exogenous abundance indexes (MMxxxxx and Axxxxx, computed from the Resource Monitoring data) are frequently significantly negatively related to the actual catch. Only for sand seatrout (SAND) do both abundance indexes enter positively. This result requires further investigation. In any event, if the fish are there, but you cannot catch them using legal recreational fishing gear, they may contribute considerably less to your value of the resource.

For several species, money spent on market goods related to the fishing day is negatively related to the catch. (And it is interesting that MON is markedly uncorrelated, at 0.03, with zip code median household income.) Site-specific fishing experience (SITETRIP) significantly increases one's catch of red drum (REDS), spotted seatrout (TROUT), and black drum (BLACK). Non-specific fishing experience (NSWTRIP) significantly increase one's catch of sheepsheads (SHEEP) and southern flounder (FLOUND), but significantly diminishes one's catch of croakers (CROAK).

PRETIRED insignificantly decreases the TROUT, CROAK, BLACK and SHEEP catch, significantly decreases the SAND catch, but has an insignificant positive effect on the FLOUND catch. People from zip codes with relatively large numbers of Vietnemase catch significantly (and substantially) fewer of several species, notable REDS, and SAND, but they catch dramatically larger numbers of CROAK. People from urbanized areas catch fewer REDS, but more CROAK, SAND, and FLOUND. Texas natives (or at least people from areas where relatively more people are Texas natives) catch significantly fewer REDS, but more TROUT, CROAK, BLACK, and FLOUND. If more of your neighborhood is employed in fishing, farming or forestry, you tend to catch significantly more REDS, SAND, and SHEEP, but significantly fewer CROAK. Higher neighborhood incomes mean higher REDS catch, but significantly lower CROAK and SAND catch rates. These differing results undoubtedly reflect the "sport" versus "food" values of different species.

These tendencies might still reflect regional variations in fishing location, which might be correlated with demographic factors. To identify non-specific geographical and seasonal variations in catch rates, we also estimate OLS regressions of actual catch rates on a set of major bay dummies, MJ1 - MJ8, and a set of monthly dummies, MN5 - MN11 (where MN5 is May 1987, etc.). The results of these regressions are displayed in Table A.2. Clearly, there is considerable qualitative geographical and seasonal variation in catch rates for all species. Table A.3 therefore includes the quantitative variables from Table A.1 (with the exception of Axxxxx, which takes on only one value per bay system), as well as the set of dummy variables MJ1 - MJ8. Geographical variation in resource stocks does not seem to explain completely the observed variations in catch rates. Tastes (demographics) still seem to matter in many cases.

Since the abundance indexes derived from the Resource Monitoring data set do not seem to be a very good proxy for expected annual catch, we revert to using the information present in the contingent valuation sample. With over 5000 usable responses, we can average the actual current catch data for each respondent across all fishing trips to a particular bay system in a particular month. Likewise, we can generate annual average actual catch rates in each bay system. Tables A.4a through A.4c describe catch data based on the CV sample information. Table A.4a displays the differences in mean catch rates across bay systems for each species (AAxxxxx). Table A4.b explains the actual individual catch for each species using both monthly average catch rates and “annual” (May through November) catch rates, plus a variety of demographic variables. The monthly average catch is clearly the preferred indicator when both are included. (Its coefficient is always near one and highly significant.) However, if only annual catch rates are included, as in Table A.4c, these do an excellent job of explaining current individual catch. But sociodemographic, “experience,” and market expenditure variables still contribute significantly to explaining individual catch rates for several species. In words, you don’t just catch what everybody else catches--who YOU are makes a difference too.

In subsequent work, we will contemplate using regression models like these to generate fitted reduced form estimates of individual catch to be used as explanatory variables in the logistic regression models for the demand equation. Purging catch rates of components which might be correlated the error term may improve the accuracy of the estimated coefficients.

7. Explicit Trip Motivation, Trip Goal Satisfaction

The main objective of this project is to determine whether water quality has any statistically discernible effect upon the value of access to a recreational fishery. For a subset *of* respondents--those who were interviewed prior to embarking on their fishing trip--respondents were actually asked explicitly about how important it was to them to be able to "enjoy natural and unpolluted surroundings" on a fishing trip. The responses warrant investigation.

In the pre-trip interviews, the TPW survey actually asked direct questions about a whole variety of potential motivations for going fishing. All respondents were asked to respond on a 10-point Likert scale (with 10 being "extremely important" and 0 being "not at all important") the importance they place upon recreational fishing as away to:

A - Relax (PRERELX)
B - Catch Fish (PRECAT).

The third motivation question was drawn at random from a selection of alternatives, including:

C - Got Away from crowds of people (NOPEOPLE),
D - Experience unpolluted natural surroundings (NOPOLLUT),
E - Do what you want to do (DOWHTWNT),
F - Keep the fish you catch (KEEPFISH),
G - Have a quiet time to think (QUIETIME),
H - Experience good weather (GOODWTHR),
I - Spend time with friends or family (FWDFMLY), and
J - Experience adventure and excitement (ADVNEXCT).

Since the latter eight goals were not asked of everyone, it was necessary to focus on the subsamples to which each question was posed. For pre-trip interviews which were not matched with post-trip interviews of the same anglers, we have a very limited amount of information. It is not possible to include demographic data, because zip codes were not collected. We therefore rely on whether the professed target species was red drum, trout, or flounder (TARGR, TARGT, or TARGF), upon major bay dummies, monthly dummies, and upon a dummy variable for weekend days. We use OLS regression of the recorded Likert scale response on these variables in an effort to detect factors affecting angler’s objectives in going fishing. The results are contained in Table A.5.

From Table A.5, we see that target species, geographic dummies, and seasonal dummies do not help at all to explain the NOPOLLUT motivation for going fishing. However, the target species do affect the NOPEOPLE motivation, the KEEPFISH motivation (red drum anglers seem to fish for sport; flounder anglers fish for food), and the GOODWTHR motivation (trout anglers enjoy the weather more; red drum and flounder anglers are less inclined to go out for the nice weather. . they must be more serious). Red drum anglers are less likely to go fishing for its social aspects (FRNDMLY).

More weekend anglers claim to be strongly motivated by the desire for adventure-and excitement (ADVNEXCT). Geographical and seasonal dummies occasionally make significant differences in the objectives of anglers. However, the values of the F-test statistics corresponding to these regression suggest that none of the models have particularly good explanatory power.

Unfortunately, people who were interviewed prior to their” fishing trips were not a random sample of anglers. Interviewing personnel did not begin to collect data until 10:00 a.m. in general, so pre-trip interviews sample individuals who do not embark on fishing trips until relatively late in the day. These are probably less avid fishermen. Consequently, what we learn from this sample cannot be reliably extrapolated to the entire sample. (It would have been helpful if the pollution question, in particular, had been posed to everyone, both pre- and post-trip.) Nevertheless, with this caveat in mind, we can examine the apparent relationships between attitudes and other variables.

For the pre-trip interview sample which could be matched with corresponding post-trip interviews, we have both the attitudinal variables and the crucial zip code data which allow us to splice in data (by zip code) on our primary Census variables: median household income (HHLDINC). proportion of the population over 65 (PRETIRED), proportion of the population with birthplace in Texas (PTEXNATV), the proportion living in urban areas (PURBAN), the proportion *of* the population reporting Vietnamese origin (PVIETNAM), and proportion of the population speaking Spanish ●t home ●nd speaking English not well or not at all (PSPNOENG). If we assume that zip code ●reas are relatively homogeneous, we can use median household income and these demographic proportions to control for ●certain extent for the respondents demographic characteristics. To determine the ●xtent to each motivation depends upon the characteristics of the respondent, we can attempt to interpret a number of OLS regressions. Other included explanatory variables are: number of fishing trips to the interview site over the last year (SITETRIP), number of saltwater fishing trips to other sites (NSWTRIP), and money spent on market goods during this fishing trip (hION). The results are presented in Table A.6.

In the post-trip interviews, the TPW survey asked some direct questions concerning respondents' ability to achieve certain goals in going fishing.

Again, all respondents were asked to respond on a 10-point Likert scale (with 10 being "completely" and O being "not at all") the extent to which they were able to achieve the same set of goals (A through J). All respondents were offered the first two goals, and one question from the remaining eight was asked of each respondent.

In subsequent research, we may devote attention to the other attitudinal questions in the post-trip surveys, but for the present we will focus on the NOPOLLUT question, since this is most relevant to the issue at hand. For post-trip respondents' answers to the question "To what extent were you able to experience unpolluted natural surroundings," we obtained the regression results summarized in Table A.7. This OLS regression demonstrates that *who* you are (the demographic variables) has little to do with your perception of your ability to enjoy unpolluted surroundings. The only exception may be the PVIETNAM variable. On the other hand, geographic and seasonal dummies occasionally make ● statistically significant contribution to explaining peoples responses. Anglers do seem to have differing perceptions of the level of pollution, especially across bay systems. The northern bays are perceived to be more polluted than are southern bays.

It is unfortunate that this attitude question (NOPOLLUT) was not asked of the entire sample, so that this variable could be employed as a potential explanatory for annual resource values. Nevertheless, we can experiment will a logistic regression specification based upon the 830 respondents who were posed both the NOPOLLUT question ●nd the contingent valuation question. Table 5 summarizes the results of an ordinary logit model (without water quality variables or catch data) which includes the Likert scale value for the NOPOLLUT variable as a potential shift variable for the demand function.

Table 5

Alternative Strategy: Use Reported Pollution Perceptions to Explain Value
(n- 830)

Variable	Est. Coeff.	Asy. t-ratio	Demand f“ q
LOFFER	-0.6639	-10.22	
LTRIPS	0.4145	5.946	-
LINC	0.3966	0.9774	1.590
MON	0.004663	3.901	0.01869
TOTAL	0.003468	0.2962	0.01390
PSPNOENG	0.2828	0.1820	1,134
PVIETNAM	4.228	0.2686	16.95
PURBAN	-0.2009	-0.8602	0.8051
NOPOLLUT	0.07043	1.753	0.2823
constant	0.08104	0.02007	-
log(p)	-	-	-2.661

max LogL - -357.53

Since only a tiny subsample of the full dataset is being used in this case, we might expect some differences in the implication of the fitted models (especially if there was anything non-random regarding the choice of whom to ask each of the trip satisfaction questions--a factor which has not yet been investigated) . However, the implied demand derivatives in Table 5 are highly consistent with those derived using the full dataset, except for the fact that the coefficient on PSPNOENG changes sign. The price elasticity of demand is typical, at -2.66; the income elasticity of demand is somewhat higher than in the full sample, at 1.589. However, in this subsample, the level of significance of LINC has dropped somewhat.

Of particular interest is the coefficient on NOPOLLUT. This variable is statistically significant at the 10% level in the logit model. Adjustments in aspects of environmental quality (including water quality) which would increase a respondents' Likert scale choice by 1 unit (on the scale of 1 to 10) would therefore seem to increase the log of fishing days demanded by 0.28. Since the mean Likert scale value is approximately 8.2, this implies that the "elasticity of fishing day demand with respect to environmental quality" is roughly 2.2--an elastic response,

8. **Perceptions of Pollution versus Measured Water Quality**

When we choose to specify ● resource valuation model using water quality measures as explanatory variables, we are not being specific about whether water quality ● ffects valuation of the recreational fishery directly or indirectly. For example, anglers *may* have no conscious perception of the dimensions of water quality when they go fishing, but water quality may be " closely related to fish abundance and therefore to catch rates, so that water quality variables are proxies for other variables which do enter directly into individuals' utility functions. (At present, we are exploring OLS regression models for catch rates which include water quality variables.)

To determine whether perceptions of environmental quality reflect actual levels of measured dimensions of water quality, we can select the subsample of respondents who were queried regarding their ability to enjoy unpolluted natural surroundings. We can then regress the NOPOLLUT variable on a range of water quality variables to see whether any statistically significant relationships emerge. If anglers appear to perceive water quality directly, then we can argue that water quality probably enters directly into their utility functions as a detectable resource attribute. If not, we would be inclined to say that appreciation of water quality variables is implicit, acting through other variables which are manifestations of water quality.

Results for this experiment are given in Table A.8. There are 695 observations for which complete data exist for the initial set of explanatory variables we use here, Once again, monthly or annual averages for each bay system are used for the water quality variables, rather than conditions actually existing in the area on the specific day when the NOPOLLUT survey response was collected. This averaging process may considerably obscure an underlying close relationship between the date- and site-specific values of the water qual~ty variables, had we been able to collect this information simultaneously with the creel survey. Consequently, the standard error for the parameter estimates may well be larger than they would be with more accurate data. Therefore t-tests for the statistical significance of coefficients are probably not conclusive.

Table A.8 shows that several water quality measures bear "estimated coefficients with t-values greater than unity. The two different measures of dissolved oxygen, MDO and DISO (from different data sources) enter oppositely and relatively significantly. Water transparency (TRANSP) significantly improves perceptions of low pollution. NH4 and PHOS and CHLORA are positively correlated with these perceptions; NITR is *negatively* related. CHROMB and LEADB detract from perceived environmental quality. (Other specifications reveal the consequences of the high correlations between OILGRS and LEADB: one or the other used alone is strongly negatively significant, but not both.)

A tentative conclusion from these initial models is that people do seem to have perceptions of environmental quality that are somewhat related to actual measured dimensions of water quality. Loosely, then, policy actions designed to change the levels of arguments which probably figure significantly in regressions like that in Table A.8 will change anglers' perceptions of pollution levels. The censored logistic regression reported in Table 5 could then be used crudely in a "second stage" to infer the effects of such policies on the demand for fishery access and on the total social value of the fishery.

9. Tentative Findings and Directions for Continuing Research

At this stage, of course, the results we have obtained reflect only our "first pass" through the data, to determine whether statistically discernible relationships among the variables of interest will assert themselves. Having achieved some success, it Is now necessary to go back over all the data to verify the plausibility of the observed values ●nd to "clean" the sample of additional influential observations which may be causing varying degrees of mischief in the ●stimation process. Occasional questionable values emerged during the work thus far. 'Usually, the statistical fit of the models is improved by correction of these problems.

Some remarkable outliers among the water quality data on bottom deposits from the Department *of* Water Resources need to be examined before these "parameters" are included in the model. We also need to splice in the water quality data obtained from the Texas Water Development Board. Due to the absence of a crucial map, we are not able at present to distinguish accurately between the data for the Upper and Lower Laguna Madre areas. With that problem resolved, we will have at our disposal a number of other important dimensions of water quality.

With tighter data, we will be able to employ the more refined econometric methods described in sections 2.2 and 4.2 of the paper. For now, we have been satisfied to obtain point estimates of the demand function parameters and to rely upon the statistical significance of the underlying MLE logit parameters to imply the significance of the corresponding demand function parameters.

As is typical with survey analyses, the process of utilizing a data set reveals many ways in which the questionnaire could be improved from the point of view of using its results for particular tasks. We find that these data would have been much more useful if the range of ***offered*** threshold values had been manipulated during the course of the survey to ensure that fairly even proportions of "yes" and "no" responses were elicited. The efficiency of the estimation process is greater when one is better ●ble to discriminate the shape of the distribution in the vicinity of the marginal mean of the distribution of implicit valuations. This sample has a disproportionate number of "no" responses, which means that the information we have frequently concentrates on the upper tail of the distribution, which is less helpful.

For the pollution aspect of this study, ***our*** objectives would have been helped by asking ●ll respondents direct questions about their water pollution perceptions and explicitly whether these perceptions affect their enjoyment of the fishing day (today or over the course of the year).

It would have been desirable to elicit retrospective information from. respondents on their approximate total annual catch of each species, their self-assess fishing ability, and especially, their target species (this was only asked in pro-trip interviews).

We need to know more about the econometric literature on utilization of group means in lieu of individual values for explanatory variables. Since some of our earlier work with San Francisco Bay area data (Cameron and Huppert, 1988a, 1988b, and 1988c) has implied that individual income, for example, is correlated with Census median zip code income only at a level of roughly 0.3 to 0.4, much information may be lost by using these medians as proxies. On the other hand, there may be some valid arguments for treating zip code median income as a reasonable measure of "permanent income," or the operational level of total consumption for the individual relative to neighbors. This methodological issue still need to be explored. As we have pointed out in the paper, if information is being obscured by the use of group means or medians, the standard errors of the point estimates in our models could be artificially amplified, making parameters appear to be statistically insignificant at any of the typical (arbitrary) levels. With "real" data, the proxied variables might be strongly statistically significant. We don't know.

A major unresolved issue,which has confounded us for some time, is the apparent negative effect of catch rates for some species on resource values. This is counerintuitive, since we have strong priors that better catch rates should imply a more desirable resource. We ●re confident that some explanation can be found. Certainly, five thousand Texans cannot be wrong.

Effort thus far has been focused on determining the parameters of the demand functions corresponding to the fitted total valuation functions for a year of fishing access. The basic implications of macroeconomic theory for the parameters of a log-log demand specification are readily satisfied. The price elasticity of demand for fishing days (if a market existed) appears to be roughly -2.2; the income elasticity appears to be just less than unity, implying that recreational fishing is borderline between being a necessity and a luxury. It is unfortunate that the lack of specific demographic data on our respondents prevents us from unambiguously identifying respondent characteristics which would let us segregate the sample and estimate separate demand functions for each group. We must content ourselves with using zip code averages as "shift" variables for a common demand specification.

Geographical heterogeneity in the demand for recreational fishing days does seem to exist. Water quality variables seem to explain quite a lot of this geographic variation. The Vietnamese seem to have markedly different preferences for fishing than the population as a whole. Money spent on associated market goods, once thought to be • reasonable proxy for the non-market value of a fishery, is positively related to the value of fishing day (but typically completely unrelated to catch success). Importantly, many other explanatory variables make strong contributions to explaining the annual value of fishing day access; reliance solely upon market expenditures could severely misstate resource values.

APPENDIX I

NONLINEAR OPTIMIZATION OF THE CENSORED LOGISTIC REGRESSION MODEL

a.) Gradients and Hessian Elements for Nonlinear Optimization

For the simplest version of the model, with $g(x_i,\beta) = x_i'\beta$, we can write out these derivatives by first defining the following simplifying abbreviations:

(1) $\psi_i = (t_i - x_i'\beta)/\kappa \qquad R_i = 1/(1+\exp(-\psi_i)) \qquad S_i = R_i^2\exp(-\psi_i)$

The gradient vector for this model is then given by:

(2) $\partial \log L/\partial\beta_r = \Sigma\, (x_{ij}/\kappa)\, ((I_i - 1) + R_i) \qquad r = 1,\ldots,p$

$\partial \log L/\partial\kappa = \Sigma\, (\psi_i/\kappa)\, ((I_i - 1) + R_i)$

The elements of the Hessian matrix are:

(3) $\partial^2 \log L/\partial\beta_r\partial\beta_s = -(1/\kappa^2)\ \Sigma\, x_{ir}x_{is}\, S_i \qquad r,s = 1,\ldots,p$

$\partial^2 \log L/\partial\beta_r\partial\kappa = -(1/\kappa)^2\ \Sigma\, x_{ir}\, ((I_i - 1) + R_i(1 + \psi_i)) \qquad r = 1,\ldots,p$

$\partial^2 \log L/\partial\kappa^2 = -(1/\kappa^2)\ \Sigma\, (2\psi_i)\, ((I_i - 1) + R_i) + \psi_i^2 S_i$

The expectation of I_i is $[1/(1+\exp(\psi_i))]$. The negatives of the expectations of the Hessian elements are as follows:

(4) $-E(\partial^2 \log L/\partial\beta_r\partial\beta_s) = (1/\kappa^2)\ \Sigma\, x_{ir}x_{is}\, S_i \qquad r,s = 1,\ldots,p$

$-E(\partial^2 \log L/\partial\beta_r\kappa) = (1/\kappa^2)\ \Sigma\, x_{ir}\psi_i\, S_i \qquad r = 1,\ldots,p$

$-E(\partial^2 \log L/\partial\kappa^2) = (1/\kappa^2)\ \Sigma\, \psi_i^2\, S_i$

For models with more general forms of the valuation function, $g(x_i,\beta)$, the gradient vector and Hessian matrix will have different formulas. In these situations, it may prove easier to substitute computing time for programming effort by using numeric derivatives in the optimization process.

b.) *Standard Error Estimate for Logistic Regression Parameters from Ordinary MLE Logit* Algorithms

One alternative is to use Taylor series approximation formulas for the variances of the desired parameters (Kmenta (1971, p. 444)):

(5)
$$\mathrm{Var}(\kappa) - \mathrm{Var}(-1/\alpha) = [1/\alpha^2]^2\ \mathrm{Var}(\alpha)$$

$$\mathrm{Var}(\beta_j) - [\gamma_j/\alpha^2]^2\ \mathrm{Var}(\alpha) + [-1/\alpha]^2\ \mathrm{Var}(\gamma_j) + 2\,[\gamma_j/\alpha^2][-1/\alpha]\ \mathrm{Cov}(\alpha,\gamma_j)$$

A second possibility is to use the analytical formulas for the Hessian matrix given in (3) in conjunction with the optimal values of β and κ derived from γ^*. The negative of the inverse of this matrix can be used to approximate the Cramer-Rao lower bound for the variance-covariance matrix for β and κ. Alternately, the expected values of the Hessian matrix elements are sometimes used in this process.[7]

Whichever way the point estimates ●re obtained, ●nd by whatever method the asymptotic standard errors are determined, these ingredients are necessary for hypothesis testing regarding the signs ●nd sizes of individual β_j parameters. These can frequently be interpreted as derivatives (or as elasticities) of the inverse demand function (or ad hoc "valuation" function), and assessments of their probable true values are can be an important objective in many empirical investigations.[8]

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[7] The outer product of the gradient vector evaluated at the optimum is also sometimes used. However, since the expectation of the Hessian has simple formulas, it is probably preferred in this application.

[8] Of course, if estimates are achieved by optimization of (10), hypothesis testing regarding the βs (individually or jointly) is the same as in any maximum likelihood context: by likelihood ratio tests.

APPENDIX II

CONSTRUCTION OF ESTIMATING SAMPLE DATA

1. <u>Observations from the Texas Parks and Wildlife Survey</u>

The "high use" season data set from the survey covers primarily the period from May 1987 to November 1987, although a few observations are included for December, 1987 and for January and February, 1988. We begin our analysis with the 9413 responses collected in post-trip interviews alone. Relatively fewer respondents were interviewed before their outings, since survey interviewers arrived later in the morning than most anglers leave for fishing trip. Also included are the 1094 respondents who were interviewed both before and after their fishing trip. These respondents were also posed the contingent valuation question; they will also b. systematically different types of individuals because all are characterized by departing typically later in the day. This may be related to their implicit resource values.

Variables from the survey which are available for use in this study include the following:

MAJOR	which of eight major bay systems (1 -north; 8-south)
HOLIDAY	whether the surey day was a holiday
DAYTYPE	1st digit (holiday) 2nd digit (day of week)
MONDAY	year/month/day
MINOR	code identifying minor bay where survey was conducted
STAT	numerical code identifying survey site
ID	boat ID number
INTTIME	interview time
TRIP	
ACT	●ctivity- recreational fishing or partyboat fishing
PEOPLE	number of people in the party
COUNTY	code for county or state of residence
MINBAY	minor bay where most fish were caught
GEAR	type of fishing gear usedby party
BAIT	type of bait which caught the majority *of fish*
REDS	number of red drum landed
LRED	largest specimen landed and measured
MLRED	average length of <-6 specimens landed and measured
TROUT	number of spotted seatrout landed
LTROUT	"

MLTROUT	"
CROAK	number of croakers landed
LCROAK	
MLCROAK	
SAND	number of sand seatrout landed
LSAND	
MLSAND	
BLACK	number of black drum landed
LBLACK	
MLBLACK	
SHEEP	number of sheepshead landed
LSHEEP	
MLSHEEP	
FLOUND	number of South Atlantic flounder landed
LFLOUND	
MLFLOUND	
TOTAL	total landed, all species
LTOTAL	
MLTOTAL	
SWTRIP	number of saltwater fishing trips made in the last 12 months
SITETRIP	number of trips to the survey sight in last 12 months
FWTRIP	number of freshwater fishing trips in last 12 months
SATISFY	overall grade given to the fishing trip (0-10)
POSTRELX	answer to the post-trip question on extent person was able to relax
POSTCAT	answer to the post-trip question on extent person was able to catch fish;
POSTVAR	answer to alternating questions on other dimensions of fishing trip
ZIP	five-digit zip codes which will be used to merge survey data with census tract information on zip code areas for the ●pproximately 90% of the sample with Texas residency implied. "What is the zip code where you currently live?"
MON	dollars spent on the fishing trip for non-capital market purchases: "How much will you spend on this fishing trip.from when you left home until you get home ?"
CONTVAL	conveys the arbitrarily assigned threshold value proposed to each respondent ●nd their yes/no response to the question: "If the total cost of all your saltwater fishing last year was dollars more, would you have quit fishing completely?" A "no" response therefore implies that the resource value is greater than the threshold.

While the data set was quite well checked for consistency prior to our receipt of it, several unusable observations had to be deleted. Criteria for deletion were:

- missing data on the contingent valuation question;
- erroneous codes for the relaxation or catch satisfaction questions;
- inadmissible codes for the post-trip varying satisfaction-oriented questions;
- inadmissible levels for the relaxation or catch satisfaction questions;
- inadmissible values for the response to the contingent valuation question:
- more than 365 reported saltwater or freshwater fishing trips reported over the last year;
- fractional numbers of salt- or freshwater fishing trips reported;
- negative or greater than 365 trips per year;
- satisfaction Likert scale values outside the 0-10 integer range;
- trout catch greater than 300, total catch greater than 300;
- zip codes greater than 99999;
- no average abundance figures for this month or bay system.

If preliminary specifications on this data set indicate that certain variables appear to have no statistically discernible effect on valuations, the presence or absence of valid values for these variables will be irrelevant, and some of these observations can be reinstated.

Initial specifications do not incorporate sampling weights to offset any bias in estimated valuations which could result from systematic deletions of observations upon criteria which are correlated with resource values. If necessary, weights will be incorporated in subsequent specifications.

2. Controlled Catch Rate Data. Resource Monitoring Data Set

Another requirement of this study is some measure of "expected" catch rates by time and location. Actual catch associated with the fishing excursion during which the survey responses were collected are at best an imperfect indicator of catch expectations. Contemporaneous catch effects are also confounded by the possibility that the angler's expertise is unmeasured, and this expertise will simultaneously affect both their valuation of the resource and their current catch. This will result in misleadingly large estimates of the impact of catch rates on the total value of the year's access to the sportfishery if expertise, catch and resource valuation are all positively correlated (which seems likely).

In order to avoid the omitted expertise variable's biasing effect on the catch rate coefficient, we take advantage of a supplementary data source which can be merged with the survey data. The Texas Department of Parks and Wildlife regularly collects information on individual species abundance, sizes, tagging, and other information. We elect to use this resource monitoring data for the period 1983 to 1986, for which 23,729 samples are available. Since we seek to reproduce a proxy for anglers' expectations about catch rates, the 1983-86 period would seem to provide a proxy for recent experience.

Each observation in this large data file conveys information collected during a particular controlled harvest. Variables include, gear type (3 kinds), location, date, effort (which depends on gear type), meteorological data (including winds, cloud cover, rain, fog, water temperature, water depth, turbidity (TURB), salinity (SAL), dissolved oxygen (DO), barometric pressure, tide information, and wave height. The gear is applied to the fishery for a measured period of time. At the end of the sample period, the gear is removed and a count is taken of each type of organism collected. Mean lengths are also available. We focus on information for the major recreational target species of finfish: red drum (REDS), croaker (CROAK), black drum (BLACK), spotted seatrout (TROUT), sheepshead (SHEEP), sand seatrout (SAND), and southern flounder (FLOUND).

In distilling this information into a catch expectation variable for each species, several manipulations are required. *First, we* standardize the catch using each of the three gear types to the mean number of effort units for each gear type. This controls for variations in catch rates due solely to differing sampling durations, yielding catch per unit effort (CPUE) for each type of gear, for arbitrary effort units.

Once these "catch per unit effort" (CPUE) figures have been obtained, we compute overall means and standard deviations in CPUE for each species by *gear type.* We then use these means and standard deviations to "standardize" the individual CPUE figures for each species and each gear type. The resulting quantities are "indices" of CPUE. The different gear types do not necessarily yield additive estimates of catch rates, since they differ in effectiveness for any given number of hours of application. Therefore, we must resort to the standardized indices, which are unit-free (i.e. we subtract the overall mean CPUE for each gear type, and divide through by the overall standard deviation in CPUE for that gear type).

The next step is to aggregate these indices across gear types to come up with a weighted average (across gear types) of the three indices of standardized CPUE. Our objective, initially, is to create indices of expected catch rates for each major species for each sample month and each major bay system along the Texas Coast.

The weights we use are therefore the proportion of samples collected by each type of gear in each month and each major bay system. This implies that if one type of gear was only infrequently used in a given month or bay system, the CPUE index for this type of gear will receive a very low weight in the aggregation ●cross gear types. Averages CPUE indices derived from large numbers of samples are presumed to be more reliable, and therefore receive larger weights. (DATA.CTCHIND2)

In addition to the weighted average abundance indices by major bay and month, we also computed annual average catch rates for each major bay. (DATA.ANCATCH2) Since the survey of recreational anglers asked whether they would have given up fishing entirely if the access cost had been a particular specified amount, it will also be important to consider whether annual average expected catch is a better explanatory variable for resource valuation than actual catch on the current fishing trip or even monthly expected catch around the time when the survey response was elicited. However, various different measure of catch rates will be included in the valuation models, to determine which measure, statistically, seems to have the greatest effect of resource value.

Bear in mind that the constructed abundance variables (MMxxxxx for monthly averages by bay system; Axxxxx for annual averages by bay system) are measured in standard deviation units. When these variables are used in regressions or logit analyses, the coefficient reflects the consequences of a one standard deviation change in abundance.

We may also take advantage of some of the dimensions of water quality collected along with the resource monitoring data. The 23,729 observations provides a rich quantity of information on turbidity, salinity, and dissolved oxygen. We compute average values of these measures for each month and each bay system, MTURB, MSAL, ●nd MDO (DATA.TURSALDO), to be employed in regressions of pollution perceptions on measured water quality levels.

3. **Texas Department of Water Resources Water Quality Data**

Dave Buzan and Patrick Roque of the Texas Department of Water Resources were kind enough to allow us to utilize information on the characteristics of a large number of water samples taken at diverse locations throughout the Texas estuarine/bay system for the purpose of monitoring water quality.

We use only those observations on water quality measures for which a precise quantity is given. We excluded all observations for which it was only recorded that the amount of the substance was greater than a certain amount.

For a few hundred observations, it was reported that the measured amount was less than a certain amount. For these cases, the threshold amount was very small, so we opted to record "zero" for these measures, so as not to bias upwards the mean quantities of these substances.

While occasional water samples were taken on an incredible variety of water quality "parameters," consistent sampling focuses on transparency (TRANSP), dissolved oxygen (DISO), nonfilterable residues (RESU), nitrogen/ammonia (NH4), nitrate nitrogen (NITR), total phosphorous (PHOS), and chlorophyll-A (CHLORA). There were from 816 to 3884 observations on these quality measures; the other parameters all had fewer than 100 measurements, so that monthly averages by bay system were deemed to be less reliable. For these other water quality measures (having from 90 to 100 observations), we generate annual average levels for each bay system. These measures include 'loss on ignition, bottom deposits" (LOSSIGN), oil and greaee (OILGRS), and organic nitrogen (ORGNITR). In bottom deposits, a few records are available for each bay *system* on phosphorous (PHOSB), arsenic (ARSENB), barium (BARIUMB), cadmium (CADMIUMB), chromium (CHROMB), copper (COPPERB), lead (LEADB), manganese (MANGANB), nickel (NICKELB), silver (SILVERB), zinc (ZINCB), selenium (SELENB) and mercury (MERCURB). These metals contamination data can be employed investigate whether amounts or perceptions of metal contamination appear to be statistically related to resource values.

Locational information for these samples is recorded at the level of "stations," which we identified on maps and aggregated into each of the eight major bay/estuary systems along the Texas gulf coast. Subsequent research may disaggregate further, but for now, we rely on the presumption that each bay is a reasonably isolated aquatic system. There is considerable variation across bay systems in the average levels of these "parameters." [Early models use only those "parameters" which do not seem to involve questionable "outliers" among the samples. Further investigation of these outliers will be necessary before we can be confident about using bay average levels of contamination as accurate measures of true levels.]

In sum, we have determined average levels for each of these basic water quality parameters for each bay system and for each month (DATA.DWRPARM). We also aggregate to determine annual averages for each bay system. (DATA.ANDWRPAR) For the metals and other parameters for which there are fewer observations, we have only eight observations, by major bay system. (DATA.HVYMETAL).

k. Hydrological **and Meteorological Data Collected at Survey Sites**

For each day at each survey site, TPW personnel recorded fairly detailed information about weather and surface conditions in the vicinity of the survey site. Both beginning of "day" and end of "day" values were recorded. We begin by considering only the beginning conditions (bearing in mind that this was approximately 10:00 a.m.). These data can be merged with the actual survey responses according to major bay, date, minor bay, and station numbers. Information from this data set which may prove pertinent includes:

BWINDSP - beginning wind speed;
BCLOUD - midpoints-of cloud cover categories;
BARO - beginning barometer reading;
BRAIN - whether it was raining (0 = no, 1 = yes);
BFOG - whether there was fog (0 - no, 1 = yes);
BTEMP - temperature in Celsius;

The temperature data contained obvious reporting errors, where temperatures had clearly been recorded in Farenheit instead of Celsius. Fortunately, there is very little potential for overlap in the two scales. We discredited any supposedly Celsius temperature over 40, presumed it was Farenheit, and converted it to the corresponding Celsius measure. Consistency checks confirmed chat the corrected data were feasible, give the location and times of year.

We merged these data (DATA.MDMETEOR) directly with the survey response records, based on day and location. We also constructed mean monthly levels of each of these weather and sea condition variables foreach bay system (DATA.MMETEOR), as well as annual average levels for each bay system (DATA.AMETEOR).

5. Texas Water DeveloDmen Board Water Quality Data

David Brock of the Texas Water Development Board has been very helpful in providing us with some of his agency's data on water quality. At the time of this writing, we are still seeking additional information necessary for merging this information with the other data sets. The original merge criteria contained an error.

The TWDB data measures many of the same water quality "parameters" as does the DWR data, plus some additional ones. The included data are:

Water temperature (C)
Turbidity (jksn ju)
Transparency (secchi cm)
Conductivity field @25 C-mmh
Conductivity lab @25 C - micromh
Dissolved oxygen mg/l
pH SU
Ammonia NH_3-N mg/l
Nitrite NO_2-N mg/l
Nitrate NO_3-N mg/l
NitrogenT kjeldl mg/l
Phos-T P-wet mg/l
Phos-D ortho mg/l
Organ. carbon toc mg/l
Sulfate SO, mg/l
Chlorophyll-A mg/l

These data will be incorporated with the main data set as soon as the geographical definitions can be conformed accurately.

6. <u>Health Department Data</u>

In February 1988, during a visit to Austin *to* confer with the other agencies mentioned in this Appendix, I met with Texas State Health Department data management personnel with Maury Osborn of the TPW Coastal Fisheries Branch. The Health Department maintains detailed historical records of water contamination, in particular for the purpose of determining shellfish "closures." We were informed that if a request for this data was issued by Jerry Clark of TPW directly to the Health Department, these data could be released to us. This formal request was made, but as yet, no data have materialized. We are not sure what accounts for this lack of cooperation, but we will persist.

7. **Census Data (1980) for Texas, by 5-Digit Zip Code**

The Inter-University Consortium for Political and Social Research (ICPSR) provided at nominal cost a tape containing detailed information about Texas residents aggregated to the level of 5-digit zip codes. Since all post-trip interviews attempted to collect the respondent's home zip code, we have a rich source of supplementary demographic data which we can exploit to reduce (to a certain extent) heterogeneity in valuation responses.

By far the majority of respondents (over 90% of the sample) gave zip codes within Texas. For these respondents, then, we can augment our array of potential explanatory variables for the valuation models with Census information. It is extremely important to keep in mind that zip code proportions or medians for these variables are by no means identical to the respondents' actual characteristics. At best, we might assert that since 5-digit zip codes are very small areas, geographically, it is more plausible to use zip code demographic averages than, say, county or state averages, to control for demographic heterogeneity.

The Census data which we suspect may be relevant to explain valuation responses were extracted from the Census tape and assembled in a file called DATA.TEXCENS1 . Our variables are:

HHLDINC - median household income in 1980 (TABLE69);
FAMINC - median family income in 1980 (TABLE74);
MEDINC - median individual income in 1980 (TABLE82);
PURBAN - proportion inside urbanized areas (TABLE1);
PRETIRED - proportion of individuals in zip code over the age of 65 (computed from TABLE15);
PSPANISH - proportion of individuals in zip code claiming hispanic background (computed from TABLE13);
PSPNOEN - proportion of over-18 individuals in zip code claiming to speak Spanish at home and to speak little or no English (computed from TABLE27);
PVIETNAM - proportion stating "race" as Vietnamese (TABLE12);
PFFFISH - proportion of individuals in zip code reporting to work In "forestry, fishing, or farming" sectors (TABLE66);
PTEXNATV - proportion of individuals in zip code reporting birthplace outside Texas (TABLE33).

We anticipate that household income (HHLDINC) will be the most appropriate explanatory variable reflecting income levels, although the other income measures will be explored. Since retired persons' opportunity costs of time for going fishing •ra smaller, we expect that if you come from a community with a large proportion of retired persons (PRETIRED), your likelihood of being retired yourself is larger, and your valuation of the fishery may be systematically different. The proportion of people in your zip code living in a designated urban area may also affect your motivations for going fishing, end hence your value of access.

Cultural differences In tastes and preferences (for different species of game fish, or for recreation in general) may affect valuations. Especially since some people significantly supplement their diets with "game" fish, we would like to control for these differences. The PSPANISH variable includes people who have lived in the US or Texas for several generations; the PSPNOENG variable is intended to capture the proportion of recent immigrants from Mexico, since this is by far the most prominent immigrant group in the state.

If PSPNOENG is significant where PSPMISH is not, this may reflect assimilation of the immigrant group, at least in terms of preferences regarding fish and recreation. Although this is 1980 Census data, significant numbers of Vietnamese immigrants had already settled in Texas,by that time. PVIETNAM will be slightly outdated, but may nevertheless be important. Unfortunately, the Census tapes do not seem to identify individuals which consider themselves to be a member of the prevalent “Cajun” ethnic group. PTEXNATV is the proportion of the community which reports being born in Texas, versus elsewhere. This variable ignores the cultural background of individuals, and simply discriminates the proportion of the community which may have less familiarity with Texas recreational resources, fish species, angling techniques, etc.

REFERENCES

R.C. Bishop and T.A. Heberlein, Measuring values of extramarket goods: are indirect measures biased? Amer. J. Agr. *Econom. 61, 926-930 (1979).*

R.C. Bishop, T.A. Heberlein, and M. J. Kealy, Contingent valuation of environmental assets: comparisons with a simulated market, Natural Resources J. 23, 619-633 (1983).

T.A. Cameron, "A New Paradigm for Valuing Non-Market Goods Using Referendum Data: Maximum Likelihood Estimation by Censored Logistic Regression," forthcoming, *Journal of* Environmental Economics and management, 1988.

T.A. Cameron and D.D. Huppert, "OLS Versus ML Estimation of Non-Market Resource VAlues with Payment Card Internal Data," forthcoming, Journal of Environmental Economics and Management, 1989.

T.A. Cameron and D.D. Huppert, "The Relative Efficiency of 'Payment Card' versus 'Referendum' Data in Non-market Resource Valuation," mimeo, Department of Economics, University of California, Los Angeles, 1988.

T.A. Cameron and D.D. Huppert, "Measuring the Value of a Public Good: Further Remarks," mimeo, Department of Economics, University of California, Los Angeles, 1988.

T.A. Cameron and M.D. James "The Determinants of Value for a Recreational Fishing Day: Estimates from a Contingent Valuation Survey," Department of Economics Discussion Paper #405, University of California, LOS Angeles (1986).

T.A. Cameron and M.D. James, Efficient estimation methods for use with 'closed-ended' contingent valuation survey data," Rev. ***Econom.*** *Statist.* (May 1987).

R.G. Cummings, D.S. Brookshire, ●nd W.D. Schulze (Eds.) "Valuing Environmental Goods: An Assessment of the Contingent Valuation Method," Rowman and Allanheld, Totowa, New Jersey (1986).

W.M. Hanemann, Welfare ●valuations in contingent valuation experiments with discrete responses, Amer. J. AgrEconom. 66, 332-341 (1984).

N.A.J. Hastings ●nd J.B. Peacock, "Statistical Distributions," Wiley, New York (1975).

J. Kmenta, "Elements of Econometrics," Macmillan, New York (1971).

G.S. Maddala, "Limited-dependent and Qualitative Variables in Econometrics," Cambridge University Press, Cambridge (1983).

D. McFadden, Quantal choice analysis: A survey, Ann. Econom. Sot. Measure. 5, 363-390 (1976).

R.C. Mitchell and R,T. Carson, "Using Surveys to Value Public Goods: The Contingent Valuation Method," Resources for the Future, Washington, D.C. (forthcoming, 1988).

C. Sellar, J.R. Stoll and J.P. Chavas, Validation of empirical measures of welfare change: a comparison of nonmarket techniques, Land *Econom. 61, 156-175 (1985).*

C. Sellar, J.P. Chavas, and J.R. Stoll, Specification of the logit model: the case of valuation of nonmarket goods, *J, Environ. Econom. Management 13, 382-390 (1986).*